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Spatial Analysis of Passenger Vehicle Use and Ownership and Its Impact on the Sustainability of Highway Infrastructure Funding

For the degree of Doctor of Philosophy

Is approved by the final examining committee:

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Approved by Major Professor(s): Samuel Labi

Approved by: Dulcy Abraham 4/29/2015

Head of the Departmental Graduate Program Date

SPATIAL ANALYSIS OF PASSENGER VEHICLE USE AND OWNERSHIP AND ITS IMPACT ON THE SUSTAINABILITY OF HIGHWAY INFRASTRUCTURE FUNDING

A Dissertation

Submitted to the Faculty

of

Purdue University

by

Matthew Volovski

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

May 2015

Purdue University

West Lafayette, Indiana

I dedicate this work to my wife, Jessie. She made this possible. I also dedicate this work to my family: my mother and father, Patti and Jon Volovski; and my sisters, Katie Bailie, Mary Murphy, and Susan Volovski. Lastly, I dedicate this work to my daughter, Mazie, whose impending arrival fueled all my motivation over these final months.

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The success of this dissertation is a testament to the support and guidance provided by the distinguished members of my dissertation committee: Professor Samuel Labi, my advisor and mentor for the past six years; Professor Kumares C. Sinha, my co-advisor and unparalleled expert in all things transportation; Professor Fred L. Mannering, the authority on statistical methods for transportation analysis; Professor Raymond J.G.M. Florax, who instilled in me a deep appreciation for spatial econometrics; and Dr. Loring Nies, who inspired me to pursue sustainability in the context of transportation infrastructure.

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LIST OF ABBREVIATIONS

2SLS	Two Stage Least Squares
AADT	Annual Average Daily Traffic
ATR	Automated Traffic Recorder
CLM	Centerline Miles
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
GIS	Geographic Information Systems
GMM	Generalized Method of Moments
HPMS	Highway Performance Monitoring System
IFTA	International Fuel Tax Agreement
INDOT	Indiana Department of Transportation
IRP	International Registration Plan
IV	Instrumental Variables
NHS	National Highway System
OLS	Ordinary Least Squares
PPP	Public Private Partnerships
SP	Sample Panel
UAB	Urban Area Boundaries
USDOT	United States Department of Transportation
VMT	Vehicle Miles Traveled
WIM	Weight in Motion

ABSTRACT

Volovski, Matthew. Ph.D., Purdue University, May 2015. Spatial Analysis of Passenger Vehicle Use and Ownership and Its Impact on the Sustainability of Highway Infrastructure Funding. Major Professor: Samuel Labi.

Across the United States, the sustainability of highway funding is at risk due to increasing need and uncertainty in the factors that drive revenue. Past studies on highway funding sustainability have identified that the root cause of changing highway revenue are the shifts in social demographics and economic characteristics. Unfortunately, from the revenue perspective (the focus of this dissertation), the ability of previous research to account for these factors has been rather limited in two ways; first, the inability to accurately assess current regional vehicle use (a typical prerequisite for statistical modeling of highway revenues) due to difficulties associated with collecting data for local roads; second, the inability to directly account for the spatial dependence and heterogeneity that inherently characterize vehicle use, vehicle ownership, and socioeconomic attributes.

In addressing these issues, this dissertation focuses on revenue uncertainty and investigates the socioeconomic factors that influence passenger vehicle use and ownership and, by extension, the revenue generated from this class of vehicles.

Spatial econometric models were used to capture the complex spatial trends that characterize the relationship between the influential factors and vehicle use and ownership. The models were used to estimate the impact of long-term socioeconomic changes on highway revenue from passenger vehicles.

This dissertation developed a unified framework incorporating spatial econometric modeling of regional vehicle use and ownership. This dissertation showed that vehicle use and ownership exhibit spatial dependence and heterogeneity which is caused by the influence of neighboring regions and unobserved spatial factors. Therefore, the research accounted duly for spatial heterogeneity and dependence, resulting in a more accurate and unbiased estimation. Also, the research yielded results suggesting that vehicle use and ownership are a function of the characteristics of a region as well as it neighbors.

The unified framework includes a robust methodology to estimate the current vehicle miles traveled (VMT) for all roads within a geographic region. The methodological approach uses spatial interpolation to impute unknown road segment values, overcoming an issue that typically impairs the traditional link-specific approach for estimating VMT.

This dissertation determines that, in order for the current level of funding from state gas tax revenue to be sustainable, the gas tax would have to be annually increased between 2.59% to 3.41%, depending on the forecast socioeconomic conditions. This annual increase in gas tax would allow agencies to recoup the effective fuel tax losses due changing vehicle use and ownership, inflation, and increased fuel economies. Unlike revenue from fuel taxes, revenue from passenger vehicle VMT fees is not susceptible to changing vehicle fuel efficiencies. To ensure funding sustainability, an annual VMT fee increase between 1.66% to 2.48%, depending on the socioeconomic conditions, is required; this would account for fluctuations in vehicle use and counteract the impact of inflation. The dissertation also determined that, in the likely event that a state is unable to collect VMT fees from out-of-state drivers (vehicles registered outside of the state), the fees would need to be increased by 12% to ensure funding sustainability.

CHAPTER 1. INTRODUCTION

1.1 Background

An analysis of sustainability is typically characterized as a decision between competing alternatives all with an impact on a set of considerations, typically environmental, societal, and economic. Often, the goal is to maximize the positive impacts and minimize the negative impacts, subject to financial and other constraints. This “triple-bottom-line approach,” made commonplace by John Elkington in 1987, has been generally accepted as the underlying pillars of sustainability. That same year, the Bruntland Commission began the discourse on infrastructure sustainability by publishing *Our Common Future*, which defined sustainable development as “meeting the needs of the present without compromising the ability of future generations to meet their own needs” (World Commission on Environment and Development, 1987). The core concept of sustainability is simply the ability of some entity—be that a system, object, or idea—to continue to exist on given level of inputs. However, far too often, the connection between the level of inputs and the level of sustainability of a system is not fully understood. In the context of this dissertation, the system in question is a state’s highway transportation network, and the one input most closely associated with its ability to “meet the needs of the present without compromising the ability of future generations to meet their own needs” is funding.

This dissertation defines highway funding sustainability as the extent to which a revenue source, or a mix of revenue sources, is able to meet the needed level of highway investment. First-order sustainability is herein defined as the ability of a revenue source (or mix of sources) to maintain the current funding levels considering changing socioeconomic demographics, vehicle characteristics, and inflation. In this case, future investment needs are said to be equivalent to current or historical investment outlays. Second-order sustainability is herein defined as the ability of a revenue source (or mix of sources) to provide the needed level of investment to ensure all roads and bridges meet a minimum performance threshold (performance includes condition, safety, etc.). This second approach requires an assessment of the current deficient infrastructure and a projection of future deterioration based on forecast use. Accurate assessment of future funding gaps can allow highway agencies and state and local legislatures to adjust the current tax and fee structure to ensure that the projected investment needs are met or current funding levels are maintained.

The funding for highway construction, rehabilitation, maintenance, and operations are obtained from various revenue sources. At the current time and in the foreseeable future, most highway agencies face a funding gap, which occurs whenever the funding needed for investment exceeds the revenue generated (Sinha et. al., 2005; RI SCSTF, 2011; ASCE, 2013). The increasing levels of needed funding are evident from the current state of the transportation infrastructure in the United States; roads and bridges have been assigned C- and

C+ grades, respectively, by the American Society of Civil Engineers (ASCE, 2013). The basic mechanism for generating the funds needed for the continued operation and preservation of the highway system has been largely unchanged over the previous decades. These funds are derived from numerous sources, but are ultimately collected from either system users or other sources. These include usage fees based directly or indirectly on the amount of travel (such as fuel tax or tolls), usage fees independent of travel (such as vehicle registration and licensing), and taxes generated from other sources (such as commercial or personal property tax). Funding sources that meet the changing financial needs of the transportation system while providing a fair and equitable fee structure to the system users are generally considered sustainable.

A gap in funding can appear momentary due to temporary fluctuations in revenue streams or to a short-term or unforeseen need. Incorporating this risk and uncertainty into a comprehensive infrastructure management framework can help agencies prepare for these short-term funding gaps. However, when revenue generated is consistently below the required levels, the funding gap remains and the cumulative deficit increases (Oh and Sinha, 2007); this systemic problem results in a deterioration of the infrastructure and can be viewed as leveraging of future needs through deferred reconstruction and rehabilitation. This is indicative of the current transportation infrastructure landscape where user-based revenue sources are diminishing while deterioration and need are constant or increasing.

1.2 Problem Statement

Past research related to the sustainability of transportation funding has been based on simple projections using historical transportation funding data (Congressional Budget Office, 2011). Others have attempted to draw more robust interferences by projecting revenue as a function of historical vehicle use data, such as vehicles miles traveled (VMT) and vehicle ownership (Agbelie et. al., 2010). Most transportation revenue sustainability studies identify that shifts in social demographics and economic characteristics are the root cause of shifting travel demand and vehicle use (SCDOT, 2003; Rhode Island SCSTR, 2011; INDOT 2013c); however, few have explicitly included these factors in the analysis. The ability of previous research to account for these factors has been rather limited in two ways; first, the inability to accurately assess current regional vehicle use (which is typically a prerequisite for revenue estimation) due to difficulties associated with collecting data for local roads; second, the inability to directly account for the spatial dependence and heterogeneity that inherently characterize vehicle use, vehicle ownership, and socioeconomic attributes.

A number of travel demand and vehicle use studies conducted out outside the context of transportation funding sustainability have established the link between socioeconomic factors and vehicle use and ownership. Some of these studies were carried out at the project level for link-specific roadway segments and therefore do not lend themselves to a scaled-up analysis of state-level vehicle use and subsequent revenue generation (Mohamad, 1997; Mohamad et. al., 1998; Sevear et. al., 2000; Eom et. al., 2006; NIATT, 2012). Other studies that estimated vehicle use within geographic regions as a function of socioeconomic data had resorted to using small, homogenous samples or national-level aggregation (Mannering, 1979; Griffiths et. al., 2000; Zhao and Chung, 2001; Fricker and Kumapley, 2002; Eom et. al., 2006; Kim and Brownstone, 2010; Wang et. al., 2012). In their model estimation, these studies did not incorporate spatial effects. Failure to do address spatial effects can generally introduce bias and limit the spatial transferability of models of this nature.

Spatial econometric models were used to capture the complex spatial trends that characterize the relationship between the influential factors and vehicle use and ownership. The estimated models were used to determine the impact that long-term socioeconomic changes would have on highway revenue from passenger vehicles. The estimated models account for spatial dependence and error that is inherent to the datasets.

A prerequisite to the development of spatial econometric models is a robust analysis of current vehicle use (VMT) and vehicle ownership broken down by geographical regions. Existing VMT estimation methodologies, such as the link-specific approach, have difficulty estimating VMT or traffic stream composition for road segments without corresponding travel data (this is the case for the majority of local roads). To overcome this shortcoming, this dissertation's methodological approach uses spatial interpolation to impute unknown VMT values for road segments.

Lastly, states may be unable to collect some types of passenger vehicle fees from vehicles registered outside of the state but use the state's highways. To determine what impact this would have on funding sustainability, this dissertation determined the extent of fuel purchased and travel in the state by out-of-state vehicles.

1.3 Scope and Objectives

The main objective of this dissertation was to determine the impact that long-term socioeconomic shifts would have on passenger vehicle use and ownership and, by extension, the sustainability of highway funding. Spatial econometric models were used to capture the complex spatial trends that characterize the relationship between the influential socioeconomic factors and vehicle use and ownership.

In order to complete this objective, this dissertation first assessed current vehicle use and ownership at the census tract level. This required supplementing the traditional link-specific and fuel data methodologies for estimating regional VMT with advanced spatial interpolation using Kriging estimation. Second, the dissertation investigated the socioeconomic characteristics of the census tracts, determined which characteristics have been shown in previous studies to significantly influence vehicle use and ownership, and identified which of these characteristics have been forecast to change over upcoming decades. Next, the census tract VMT and vehicle use data was estimated as a function of the socioeconomic and infrastructure characteristics of the region and its neighbor using the Durbin and Spatial Durbin econometric models. Last, the estimated models were used to quantify the impact that long-term socioeconomic changes would have on the revenue generated from passenger vehicle use and ownership. To facilitate this process, a case study was carried out for all census tracks in a selected Midwestern state.

1.4 Study Framework

This dissertation follows the detailed framework presented in Figure 1.1. The analysis begins with a robust methodology to estimate current vehicle miles traveled (VMT) for all roads within a geographic region (this data is required for subsequent econometric modeling of highway revenue). This was accomplished using advanced spatial interpolation to supplement traditional VMT estimation approaches. In addition, the percentage of the VMT that can be attributed to non-state residents was determined using extensive sampling of fuel purchase transactions and spatial interpolation.

Next, the social demographics and economic conditions considered to be the driving factors behind vehicle use and ownership, and by extension, revenue generation, were assessed. This was completed at the census-tract level, due to the comprehensive data made available by the United States Census Bureau.

The socioeconomic and vehicle use data sets were then used to develop spatial econometric models to estimate census tract VMT. The spatial modeling techniques can be viewed as an improvement over the traditional, aspatial models found in funding and vehicle use literature for two main reasons. First, spatial models were used to identify and account for spatial dependence and error inherent to the datasets. Second, the dissertation sought to establish that the VMT in a region is a function not only of the characteristics of the region but also of neighboring regions and the network as a whole. Spatial models were applied so that these lagged effects could be captured in the model estimation, allowing their influence to be quantified. The spatial socioeconomic data were then used to estimate vehicle ownership for each census tract, accounting for spatial dependence and error.

The sensitivity of vehicle use and ownership to the social and economic factors was determined and used to estimate the expected long-term change in transportation revenue in response to potential future socioeconomic shifts. This analysis was then considered in conjunction with projections for future funding needs to provide an assessment of transportation funding sustainability vis-à-vis the expected reduction in the funding gap.

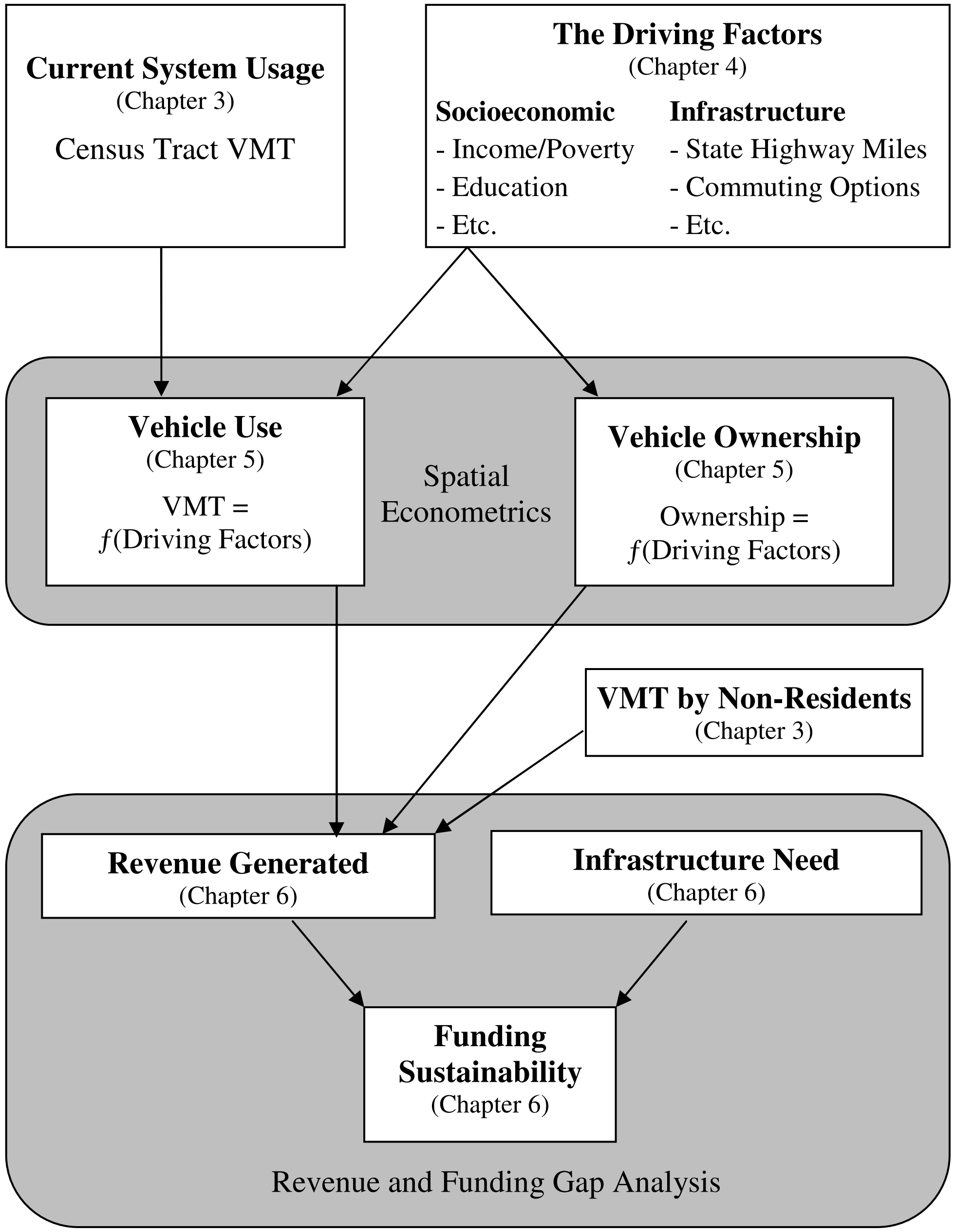


Figure 1.1 Study Framework

1.5 Organization of the Dissertation

Chapter 1 presents the historical background on state-level highway funding. It also defines the scope and objective of the dissertation and provides the methodological framework that will be followed throughout.

Chapter 2 provides a detailed summary of past highway sustainability, highway revenue, and vehicle use studies. It includes a review of the previous research approaches used to forecast transportation revenue. It also identifies and discusses the potential for current and innovative revenue sources to meet the forecasted funding needs.

Chapter 3 assesses the extent of current system usage. This examination includes the spatial interpolation of traffic stream characteristics using Kriging Estimation. This analysis provides the VMT census tract data that was required for subsequent analysis. This chapter also investigates system usage and fuel sales to out-of-state vehicles.

Chapter 4 provides a detailed description of the socioeconomic data required as input to the spatial econometric models in Chapter 5. This chapter also presents the circumstances that would result in long-term shifts in census tract socioeconomic demographics. The socioeconomic variables include census tract estimates for population, education, income, unemployment, labor markets, and commuting trends.

Chapter 5 examines vehicle use and ownership using spatial econometric models. The chapter investigates the extent to which spatial dependence and spatial error are exhibited in vehicle use and ownership. The chapter also determines and discusses the sensitivity of vehicle use and ownership to changes in socioeconomic factors and infrastructure characteristics.

Chapter 6 uses the models developed in Chapter 5 and the long-term socioeconomic trends discussed in Chapter 4 to project future transportation revenue. Revenue projections are then used to calculate adjustments to the current gas tax that would ensure that the effective level of available revenue is sustained. The projections are also used to investigate the sustainability of VMT fees as an alternative revenue source.

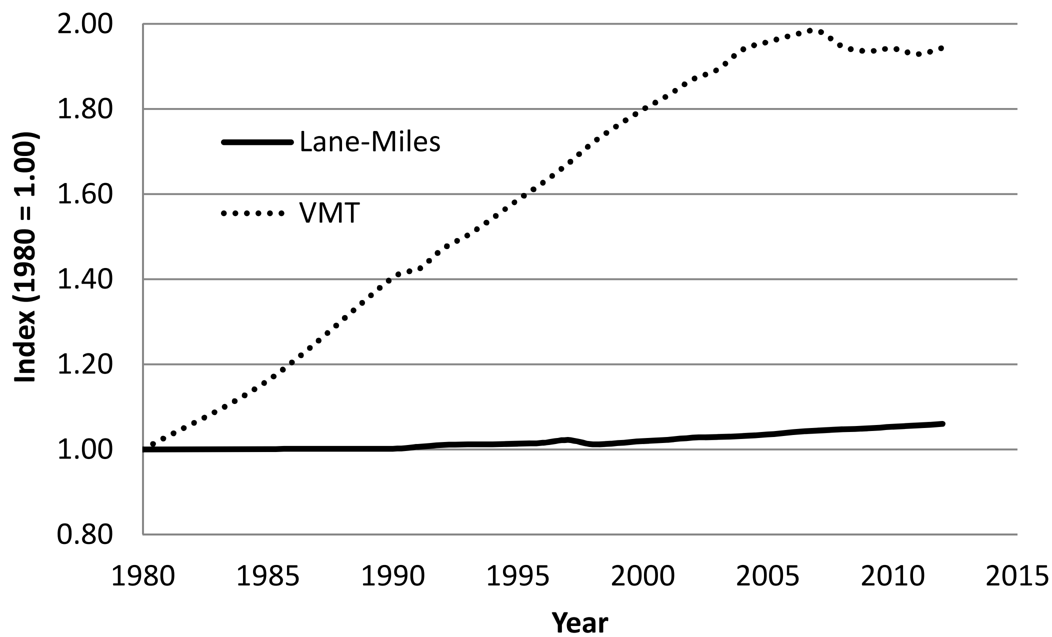
Chapter 7 summarizes the contributions and findings of the dissertation and provides directions for future research.

CHAPTER 2. LITERATURE REVIEW

2.1 Transportation Funding Sustainability

Transportation funding can be considered sustainable when a transportation agency is able to generate revenue at a rate that keeps pace with its investment needs. Investment needs include capital work (new construction and expansion), rehabilitation and maintenance work, operations, and administration. Chapter 1 introduced the concept of first-order and second-order funding sustainability, which differ based on how investment need is defined. First-order sustainability equates forecasted need to current investment outlays. Second-order sustainability defines forecasted need as the investment needed to ensure all highway infrastructure meets minimum performance thresholds. The increasing needs result from the current state of poor repair of the United States' transportation infrastructure, as evidenced by the American Society of Civil Engineer's assignment of C- and C+ grades for roads and bridges, respectively (ASCE, 2013). At the current time and in the foreseeable future, most highway agencies face a funding gap, a situation where the funding needs exceed the revenue generated (Sinha et. al., 2005; RI SCSTF, 2011).

To eliminate the deficient bridge backlog by 2028, the nation will need to invest $20.5 billion annually, which is approximately 60% greater than current funding levels (ASCE, 2013). In response to TEA-21 and MAP-21, federal, state, and local agency capital investments in highways have grown to $91 billion annually; however, that is still below the $170 billion annual capital investment needed to improve the condition and performance of all highway infrastructure (ASCE, 2013). The $79 billion gap can be attributed to greater need (due to aging highway infrastructure, deferred reconstruction and rehabilitation, and increased demand and loading due to population growth) and difficulty or unwillingness to increase revenue. An example of the increase in demand is presented in Figure 2.1. Since 1980, total system usage has nearly doubled. Over that same time, system capacity has stayed relatively constant, which has resulted in an accelerated rate of system deterioration. In Indiana, the backlog of deficient infrastructure has resulted in $3.550 billion in needed bridge repair and $3.504 billion in short-term county and city road repair (ASCE, 2013).



Centerline mile and VMT data are adapted from BTS (2012) Table 1-6 and 1-36, respectively

Figure 2.1 Demand and Capacity Growth Comparison

Most of the revenue collected by highway agencies is generated from vehicle registrations, license fees, and excise tax (predominately fuel taxes) (RI SCSTF, 2011; INDOT, 2013). These revenues are not expected to grow significantly to match needs, a prognosis that arises from recent and ongoing developments in the highway transportation environment. These developments include lower fuel consumption (due to increasing vehicle fuel efficiency and increasing percentage of vehicles that use alternative energy), consistency of the fuel tax rate, and uncertainty in travel demand forecasts.

The imminent widening of the funding shortfall has precipitated calls for new strategies for highway financing or the improvement of existing mechanisms (RI

SCSTF, 2011; INDOT, 2013). These new strategies need to help agencies achieve their financial goals of revenue adequacy, equity across the various users of the highway system, and feasibility of application from technological, cost, and public relations standpoints.

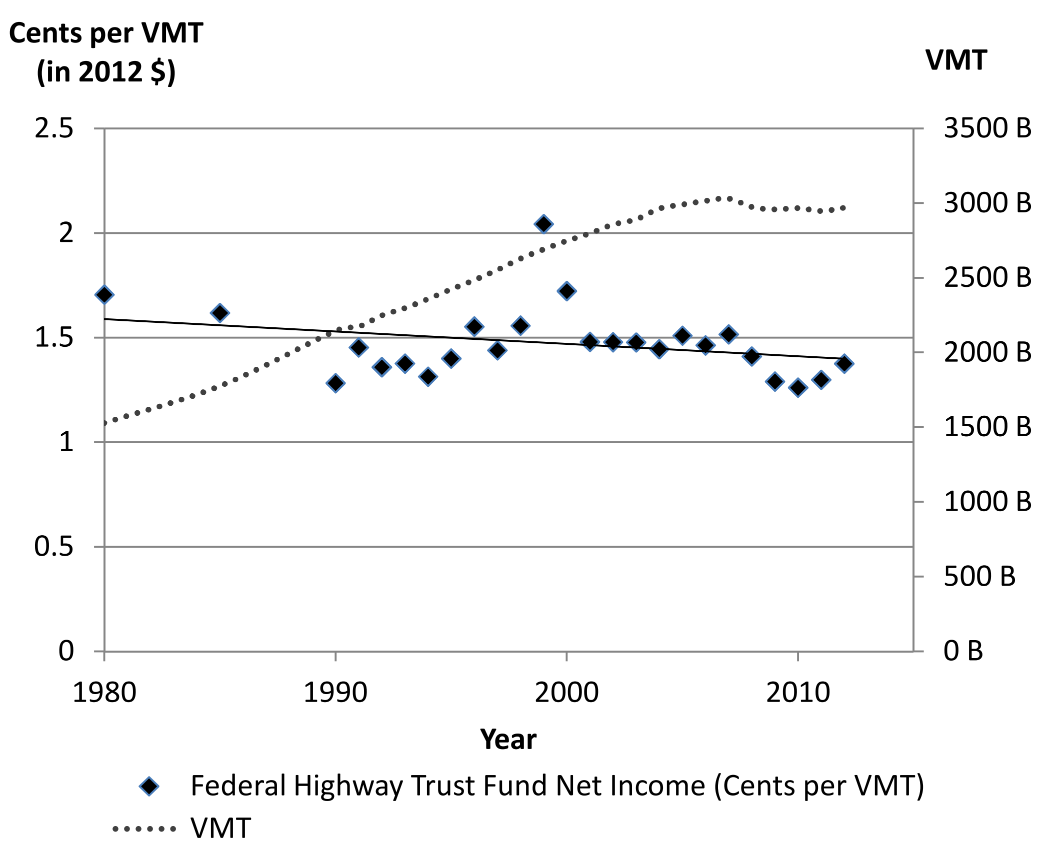
2.1.1 Obstacles to Long-Term Financial Sustainability

Current and ongoing developments in the highway transportation environment are reducing revenue and thus pose serious obstacles to the long-term financial sustainability of the current funding sources.

First is the loss of purchasing power because fuel taxes are not indexed to inflation or fuel prices. Thus, while fuel prices have increased since the late 1990s, fuel tax rates have not, resulting in a decrease in the effective fuel tax rate (FHWA, 1997). Wachs (2003) suggested that raising fuel taxes would be more effective, efficient, and equitable than other revenue-generation mechanisms. However, most elected officials are unwilling to increase gas taxes, instead opting for borrowing, using local sales tax, and other initiatives.

Second is the influx of alternative energy sources for vehicle propulsion. As alternative energies become more common, fuel taxes are not expected to generate the needed revenue for highway management (Whitty, 2003).

Third is the increased fuel efficiency, driven by regulations and consumer demand, which is resulting in lower fuel tax receipts per mile traveled (Figure 2.2). TRB (2006) estimated that with continued improvements in fuel economy, the average fuel consumption per vehicle mile can be expected to reduce by 20% by 2025.



Trust Fund and VMT data are adapted from (OHIP, 2012) Table FE-210 and (BTS, 2012) Table 1-36, respectively.

Figure 2.2 Revenue and Travel Trends

Fourth is the erosion of established finance practices. As pointed out by TRB in its 2005 special report, some potential sources of stress in highway financing are evident, particularly in certain states where the local share of responsibility is high, for example, pressures to spend portions of highway revenue on non-highway purposes.

2.1.2 Sustainability Measures

There are numerous sustainability measures and evaluation tools aimed at assessing the sustainability of transportation projects and networks. Sustainability measures include the IPAT Model, Ecological Footprint Model, Triaxial Representation of Technological Sustainability, Quality of Life/Natural Capital Model, and True Sustainability Index (Khisty et. al., 2012). Evaluation tools include Envision, GreenLITES, Greenroads, I-LAST, and INVEST, which were developed by the Institute for Sustainable Infrastructure, NYSDOT, University of Washington and CH2M HILL, Illinois DOT, and the FHWA, respectively (Labi, 2014). However, these tools are concerned with a transportation system's impact on the economy, society, and environment. This dissertation provides a methodology to determine the sustainability of the inputs required for the continued existence of the transportation system, specifically transportation funding.

2.2 Transportation Revenue

Across the nation, numerous funding sources are utilized at various levels of government. These include usage-based taxes, such as fuel and excise tax; vehicle-based fees, such as registration fees; sales tax; and other taxes, such as local property taxes (Transportation Research Board, 2011). Figure 2.3 presents the typical sources of highway revenue but should not be considered an exhaustive list. These various funding sources are then paired with numerous financing mechanisms, such as bonds, grants, loans, and public-private partnerships (Congressional Budget Office, 2011; Transportation Research Board, 2011). The ability of this blend of funding sources and strategies to meet the needs of the surface transportation infrastructure continues to diminish.

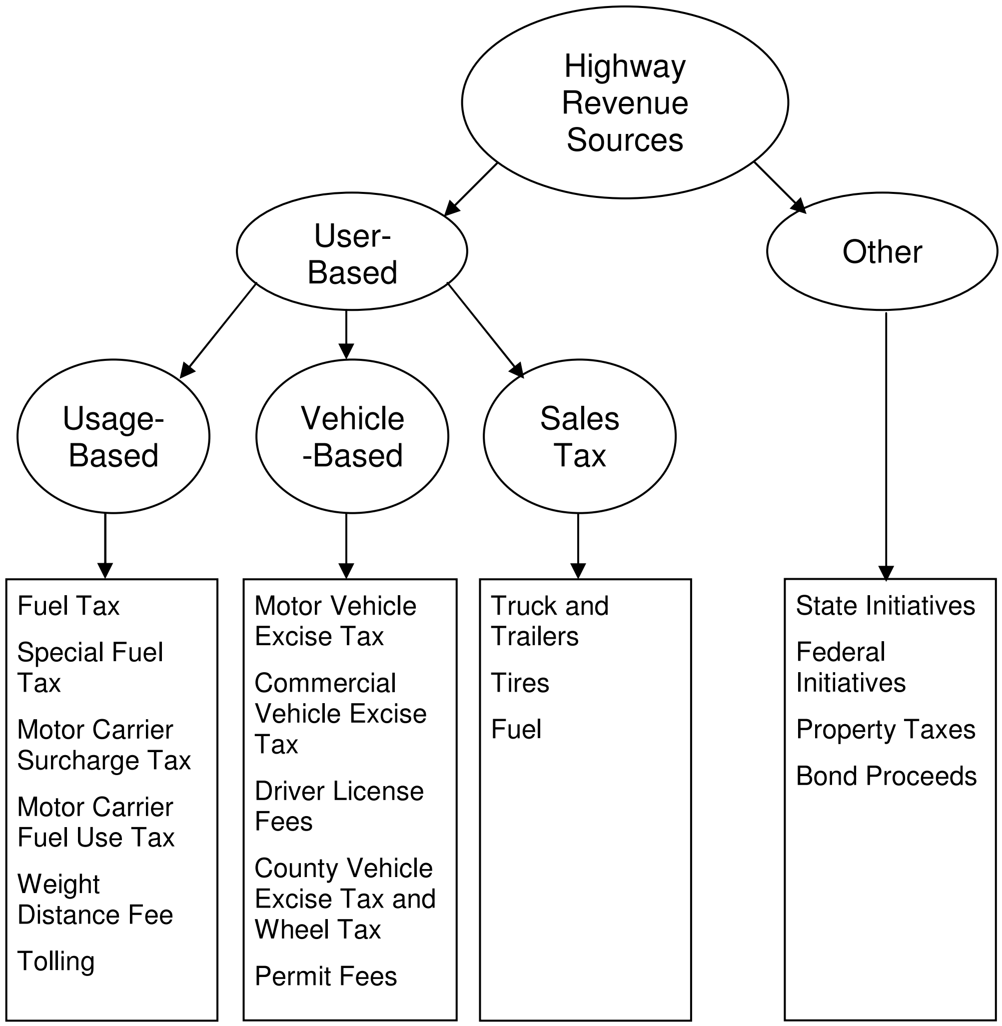


Figure 2.3 Highway Revenue Sources

One of the most prominent sources of transportation infrastructure funding is derived from fuel sales, including diesel and gasoline tax, and the heavy vehicle surcharge tax (Congressional Budget Office, 2011). The nation and thirty-six states levy a fixed-rate gas tax that, on average, has not increased in over a decade. Adjusting for the inflation in construction costs over this time period, the effective tax rate has fallen by nearly 30%, on average, across the thirty-six states. The remaining states index their fuel tax to inflation in one form or another. In some states, this is accomplished by applying sales tax to gasoline, while others directly index the gas tax to inflation or the consumer price index (Congressional Budget Office, 2011; API, 2015). Gas tax indexing allows the state to have a uniform effective gas rate from year to year; however, it does not account for the increase in VMT and therefore reduction in gas tax revenue per mile driven.

Registration and fees are paid by road users as a single (typically annual) payment for the right to operate a vehicle. These fees are graduated in terms of vehicle weight in an effort to account for highway cost responsibilities. Both fuel tax and registration tax are fairly inexpensive to administer but have problems with equity (Transportation Research Board, 2011). Registration fees do not take into account any actual road usage (VMT), whereas the fuel tax is a proxy for road usage. However, the fuel tax does not directly account for highway cost responsibility and tends to overcharge light-weight vehicles, while undercharging heavy vehicles.

2.2.1 Highway Revenue for Indiana Case Study

In Indiana, the gasoline tax rate is $0.184/gallon collected at the point of sale. The diesel tax rate manifests itself in the special fuel tax and motor carrier fuel use tax at a rate of $0.16/g. Diesel tax is prorated to reflect only the miles traveled in Indiana in accordance with the International Fuel Tax Agreement

(IFTA) (IFTA, 2013; ILSA, 2013). Trucking carriers also pay an additional $0.11/g tax on all special fuels consumed for travel on Indiana highways. In 2012, these taxes receipts totaled $814.8 million.

The motor vehicle excise tax is a registration fee paid by Indiana residents based on the initial value and age for all vehicles under 11,000 lbs gross weight. In 2012, the motor vehicle excise tax totaled $650.7 million. Heavier trucks are subject to the commercial vehicle excise tax based on a graduated scale reflecting gross weight. In 2012, the commercial vehicle excise tax totaled $61.3 million (ILSA, 2013).

Non-user based sources of revenue include state and government initiatives such as Major Moves and the American Recovery and Reinvestment Act. Further, agencies can collect revenue from property taxes and bond proceeds.

2.2.2 Transportation Infrastructure Financing Mechanisms

Transportation infrastructure financing is the act of providing the funds to pay for infrastructure construction, rehabilitation, preservation, and maintenance. Financing mechanisms such as public-private-partnerships (PPP or P3), municipal bond issuances, and infrastructure bank have the potential to reduce the costs of delivering transportation projects. However, while such financing mechanisms represent a vital set of tools in cost control, strictly speaking, they are not funding sources. All funds financed for the delivery of transportation projects need to be paid by fees and taxes collected from users and non-users of the system (The Pew Charitable Trusts, 2014).

2.2.3 Alternative Revenue Sources

Transportation administrators and researchers have long recognized the problem of inadequate highway revenue and have made efforts to address the issue from both the needs side (through better materials and design) and the revenue side (by identifying and evaluating sources of additional revenue). Reno and Stowers (1995) identified and evaluated alternatives to fuel tax, and TRB's Special Report 285 (2005) provided a comprehensive review of different revenue sources including gas tax increases, debt financing, toll pricing, and mileage charging. Also, individual states commissioned studies to identify and evaluate alternatives to the gas tax (Adams et al., 2001; Oregon, 2003; Oh et al., 2008; SCDOT, 2003). Goldman et al. (2001) and Hamideh et al. (2007) examined the efficacy of local option transportation taxes, and Verhoef and Rouwendal (2004) examined the pricing and financing in transportation networks. Wachs (2003) offered multiple reasons for increasing the gas tax, the efficacy of which was evaluated by Victoria Transport Policy Institute (VTPI, 2005).

2.2.3.1 Value tax

Value taxes are fees based on car's value that could be deductible from federal income tax, transferring tax revenue from the general budget to the DOTs. Value taxes remove some equity issues associated with flat registration fees, which have been shown to place extra burden on low-income drivers (Transportation Research Board, 2011).

2.2.3.2 Sales Tax

Sales taxes have the ability to generate large amounts of revenue in good economic times; however, they would be extremely volatile and susceptible to economic fluctuations. For example, sales tax on light-weight vehicles would be highly susceptible to economic fluctuations. In times of economic hardship, the number of new vehicles purchased reduces at a rate much faster than the reduction in vehicle usage.

2.2.3.3 Tolling

Tolling can be viewed as an efficient funding source, as it can be based on vehicle class and VMT. Tolling can be implemented to enhance mobility, and variable tolling can be used for peak period congestion relief (Congressional Budget Office, 2011). Implementation and operation costs and consumer dissatisfaction are both relatively high, but could be reduced with technological improvements such as electronic tolling. However, equity across income classes remains a concern (Transportation Research Board, 2011).

Truck-only tolling is the process of providing exclusive lanes for trucks and commercial vehicles. These lanes are financed by user fees collected at the time of use. Preliminary studies show that this approach could yield congestion relief only during peak travel times in dense urban areas (Fisher et. al., 2003; Georgia State Road and Tollway Authority, 2005). This, along with the relatively high cost of adding a lane to an urban highway, would severely limit its effectiveness in certain states.

2.2.3.4 Vehicle Miles Traveled (VMT) Fees

The Vehicle Miles Traveled (VMT) fee is a promising technique to cover the costs of highway programs (Congressional Budget Office, 2011). A VMT fee is a fee imposed on vehicle users based on the distance traveled over a defined network; in contrast, tolling charges a distance fee for a specific facility (FHWA, 2015). This mechanism could be used to offset external environmental and societal costs (reduced cost for lower emission vehicles or vehicles manufactured within the state or country). Data is currently available to establish the VMT pricing scheme: expenditure data is available from sources including FHWA's Highway Statistics; funding-needs data, from a needs assessment studies; and travel-demand data, from the states' Statewide Travel Demand Models (ISTDM).

A transportation policy may, by design or default, treat user groups differently according to residential or work locations. It is not uncommon for higher-level governments (federal or state) to subsidize highway construction in areas that have small populations. VMT fees can be used to promote funding equity. To address spatial equity, the VMT fee can be developed by decomposing the highway network into classes based on jurisdiction, functional class, or urban status (Transportation Research Board, 2011). A pilot VMT study completed in Oregon in 2009 researched the equity of variably pricing streams for urban and rural areas. The belief was that, since rural drivers drive more and do not have access to public transit, a flat VMT fee would be disproportionally severe. However, the results of the study suggested that switching from fuel tax to VMT fee would benefit those who live in rural areas more than those living in urban areas because rural drivers own less fuel-efficient vehicles (Whitty, 2003; McMullen et. al., 2010).

Equity can be incorporated in developing a VMT fee by decomposing the entire system into user groups (vehicle classes and weight groups) and facility classes (highway functional class), and establishing separate welfare functions for each of these clusters. Thus, the VMT fee can help achieve equity across vehicle modes. For example, FHWA's Highway Cost Allocation Study (1997) established that single-unit trucks over 50,000 lbs pay only 40% of the damage costs they inflict on the system, while pickups yield more revenue than the costs they incur. VMT fees can help correct such imbalances by applying appropriate fee rates for the different vehicle classes. With regard to jurisdictional and functional independence, the VMT fee mechanism allows user fee rates to be established for each jurisdictional or functional highway class to cover expenses within that jurisdiction. Several studies have proposed a two-tier VMT approach (Forkenbrock and Kuhl, 2002; National Chamber Foundation, 2005). The first tier would be collected at the state level and used to fund the construction, rehabilitation, and maintenance of the highway system. The second tier would be collected at the local level and used for congestion management.

2.2.4 Assessment of Funding Alternatives

The criteria for evaluating the highway funding alternatives includes sufficiency, economic efficiency, equity (spatial and across vehicle modes), accommodation of jurisdictional and functional independence, practicality, and ease of implementation.

First, the pricing scheme should be sufficient, in that it should generate adequate revenue not only to replace current funding sources but also to close the funding gap going forward. Second, economic efficiency considerations dictate that that the funding mechanism should contribute to the success of the highway program by helping to ensure a positive return on investment, and therefore ensure that motorists are charged prices that closely matched the cost of their road use (TRB, 2005). Third, equity in a transportation system has three facets: cost, benefit, and ability to pay (Adams et. al., 2001). Often, equity is measured on the basis of user costs due to difficulty in measuring user benefits or determining the appropriate level of regressiveness for implementation.

Fourth, in regard to jurisdictional and functional independence, it is noteworthy that the highway system in any state is typically administered and maintained by several different levels of government (the most visible of which are state and local). However, not every governmental unit is self-financed.

Lower-level governments are often subsidized by their higher-level counterparts at levels that depend on their asset inventory. Fifth, it must be practical to develop estimates for any proposed funding mechanism using available data. Lastly, it must be feasible to implement the new funding mechanism considering the additional investment in hardware, software, manpower, and other resources for administration and enforcement.

2.3 Transportation Demand

The National Conference of State Legislatures (2012) has identified several component factors that have led to changing travel demand, including a reduction in per-capita driving, increased mode share, influx of alternative fuels, and shifts in state demographics. Regional travel demand can be used to calculate the revenue that could be generated from fuel taxes, registration, VMT fees, or any other user-based revenue source. Usage-based and vehicle-based revenue is extremely sensitive to travel demand and vehicle ownership. For instance, a 5% decrease in the number of registered vehicles would result in a 5% decrease in vehicle registration revenue. The same holds true for a reduction in VMT and fuel-tax revenue (assuming the reduction in VMT is represented across all vehicles). In contrast, transportation infrastructure needs are less sensitive to changes in VMT and vehicle ownership. Much of the forecasted need can be attributed to maintenance and preservation backlogs (ASCE, 2013). Further, many costs, such as agency administration and overhead, are independent of all but large changes in system usage. In addition, recent studies suggest the percentage of pavement and bridge construction, rehabilitation, and maintenance costs contributed to traffic loading is limited (Table 2.1). This means the remaining costs are incurred due to climatic and age affects, or to non-load related infrastructure components, such as street signs, traffic signals, and safety features.

Table 2.1 Load-Related Costs

	Percentage of Load-Related Costs
Pavement Routine Maintenance[1]	
Flexible Pavement	25
Jointed Concrete Pavement	36
Composite Pavement	30
Pavement Rehabilitation[1]	
Flexible Pavement	30
Jointed Concrete Pavement	80
Composite Pavement	40
Pavement New Construction[2]	
Flexible Interstate Pavement	30
Flexible non-Interstate Pavement	25
Composite Pavement	40
Bridge Construction, Rehabilitation, and Maintenance[2]	
Average for all Bridges	66.7

1 (Li and Sinha, 2000)
2 (Volovski et. al., 2015)

2.3.1 Assessment of Current System Usage

Traffic volumes and traffic stream characteristics are driving factors in the planning, design, performance, and condition of roadway systems. Traffic studies are carried out to estimate existing traffic conditions and to forecast future traffic conditions for planned or existing roadways. The type of traffic data collected typically includes traffic volume and traffic stream composition, vehicle weights, and axle spacing. These traffic characteristics are then averaged or summed over the entire system to provide an assessment of travel within any specified jurisdiction. This dissertation uses location-specific assessments of traffic data summed over geographic regions to determine the amount of travel by the various vehicle classes. The extent of travel within a region is then used to assess the ability and efficiency of various funding structures to generate revenue at the local and state levels.

2.3.1.1 Traffic Data

The extent of road usage by vehicle class and road functional classification can be evaluated on the basis of vehicle miles traveled (VMT). Annual VMT for a given road segment is calculated as the product of the annual average daily traffic (AADT) and the corresponding segment length:

$$VMT_{ij} = AADT_{ij} \times Length_j \qquad \text{2-1}$$

where VMT_{ij} is the vehicle miles traveled for vehicle class i for segment j; $AADT_{ij}$ is the annual average daily traffic for vehicle class i for segment j; and $Length_j$ is the length of road segment j.

Agencies at all levels of government use VMT as an input in planning and performance modeling, to assess the current state of the road network and to evaluate vehicle-induced environmental impacts (Fricker and Kumapley, 2002). Furthermore, all states report VMT for all federal-aid roadways to the federal government for purposes of distributing federal transportation funds as required by the HPMS. Historically, states have used permanent traffic count stations, temporary traffic counts, and expansion factors to estimate segment VMT. Typically, data collected at state highways is of higher quality compared to that of local roads.

2.3.1.2 Traffic Counts

Due in part to HPMS requirements, all state highways and local roads receiving federal aid are covered by a network of count stations. Data is reported to HPMS in accordance with the Federal Highway Administration's (FHWA) roadway classification system.

2.3.1.3 Traffic Counting Equipment

Automatic traffic recorders (ATR) record traffic data daily. The FHWA suggests that these permanent stations should collect 24 hours of data for each day of the week for every month of the year (OHPI, 2013a). These values are then used to develop adjustment factors that are subsequently used for short-term counts (Sharma et. al., 1999; Zhao et. al., 2004; Jin and Fricker, 2008, OHPI, 2013a).

In addition to ATR stations, vehicle weigh-in-motion (WIM) detectors are used to collect long-term traffic counts. A WIM detector measures the dynamic tire pressures of vehicles in motion, which are then converted to tire loads of the static vehicle (OHPI, 2013a). There are a number of WIM technologies currently in use in the United States, including fiber optic cables, hydraulic and mechanical load cells, capacitance mats, and strain gauges. However, the most prevalent WIM instruments are piezo-electric and bending plate systems (OHPI, 2013b). In most cases, WIM technology is coupled with presence detectors (loop-detectors).

2.3.2 Vehicle Miles Traveled (VMT) Estimation

There are a number of methods to estimate VMT for road segments or networks without traffic counts. These include the fuel sales/fuel economy approach, the licensed driver travel approach, odometer readings, travel simulation modeling, regression of roadway characteristics, and state-level ratios of local VMT to collector VMT (EPA, 1999; ICF, 2004). Some—such as the fuel sales approach and odometer readings—involve a macro-level (network- or state-level) estimation, while others—such as travel simulation—are more suited for micro-level (project-level) estimation. These approaches are discussed in further detail in the following sections.

2.3.2.1 Sampling Approach

Agencies with limited resources often implement a sampling schedule in which AADT measurements are made across a relatively small but representative number of road segments sampled from a population segment comprising a given road functional class (Mohamad, 1997). This process is typically carried out for lower road functional classes using simple random sampling because such systems are relatively homogenous. For heterogeneous systems, stratified random sampling is often used to ensure that representative estimates are developed. Previous studies have stratified according to population density, per capita income, road surface type, and roadway mileage (Fricker and Saha, 1987; Mohamad, 1997).

2.3.2.2 Fuel Sales/Fuel Economy Approach

VMT estimation based on fuel sales largely depends on reliable estimation of the traffic stream vehicle composition (VMT mix) and the fleet fuel efficiencies (Vasudevan and Nambisan, 2013). These estimates are susceptible to fluctuations in fuel price. The statewide VMT is estimated using the fleet fuel efficiencies, VMT mix, and fuel tax rates.

2.3.2.3 VMT Ratio Approach

Ratios of local road VMT to collector VMT are reported in the HPMS. These ratios are developed using available local traffic counts collected by regional transportation agencies reported to the state. Counties that do not have the resources to collect local traffic data can multiply the statewide ratios by the county's total VMT for collector roads to provide an estimation of the county's total VMT for local roads. This method can be improved by regressing several known county ratios, instead of applying a single statewide ratio (EPA, 1999; ICF, 2004).

2.3.2.4 Travel Demand Modeling Approach

There are various applications of the traditional four-step travel demand model used to estimate AADT and VMT on local roads, where the cost of implementing permanent or temporary count stations at all segments is too prohibitive. All approaches use a combination of trip generation, trip distribution, mode choice, and trip assignment (Zhong and Hanson, 2009; Wang, 2012).

2.3.2.5 Regression-Based Approaches

Regression-based approaches use one or more explanatory variables to predict VMT for a given road segment. VMT estimation using regression and segment data are developed for segments where VMT data is available. Then the regression models are applied to segments with unknown VMT (Fricker and Saha, 1987; Mohamad, 1997; Mohamad et. al., 1998; Seaver et. al., 2000; Eom et. al., 2006; Castro-Netoa et. al., 2009). A second group of regression models utilizes projections of statewide data, such as the number of licensed drivers, to estimate statewide VMT (Kumapley et. al., 1994).

2.3.3 Traffic Stream Composition by Vehicle Class

VMT data is often reported for each of the 13 vehicle classes designated by the FHWA, shown in Table A.2 (OHPI, 2011; EPA, 1999). For purposes of general reporting, vehicle classes 1 through 3 are autos; vehicle classes 4 through 7 are single unit trucks and buses; and vehicle classes 8 through 13 are combination trucks. Default values at various sources, such as the EPA's Mobile 6, can be updated if additional data are available. A simple approach to updating the default values is to calculate the ratio of all heavy trucks (class 6 and above) in the traffic stream to the current national average, then multiply the ratio with the default VMT mix values. (FHWA, 2013a). A more in-depth approach involves estimating VMT mix as a function of roadway characteristics, such as lane numbers, links speed, and traffic zones (Changra et. al., 2000; Wand and Kockelman, 2009).

There is rather limited research on sampling procedures to obtain estimates for the VMT mix (distribution) across vehicle classes. One approach is to apply the Sample Panel (SP) sections used by the HMPS to estimate the K factor and directional factor (OHPI, 2013b). The precision required for sampling depends on the road functional class as seen in Table 2.2. A confidence-precision specification of 90-5 means that 90% of the time, the estimate is expected to fall within 5% (plus or minus) of the true value.

Table 2.2 Confidence Interval and Precision Specifications for AADT Sampling (HPMS Field Manual, 2013)

	Interstate	Other Freeway and Expressway	Other Principal Arterial	Minor Arterial	Major Collector	Minor Collector
Rural	90-5	90-5	90-5	90-10	80-10	-
Small Urban	90-5	90-5	90-5	90-10	80-10	80-10
Urbanized < 200,000 population	80-10	80-10	80-10	80-10 or 70-15	80-10 or 70-15	80-10 or 70-15
Urbanized ≥ 200,000 population	90-10	90-10	90-10	90-10	80-10	80-10

A second approach to estimate VMT mix for locations without VMT mix data is to use a geostatistical weight-distance-based algorithm. One such method is Kriging estimation, which utilizes the spatial distance and autocorrelation between data collection sites and the location of interest to impute unobserved data values from known data (Cressie, 1993; Wackernagle, 1995). This methodology is discussed in Chapter 3.

2.3.4 Transportation Revenue and Demand from Out-of-State Vehicles

Research that has investigated the percentage of VMT and fuel sales attributable by vehicle origin (in-state vs. out-of-state) is extremely limited (Sinha, 1979; OG, 2012). In general, the findings from past studies suggest roughly a 70/30 split; however, there is a need to develop a new methodology for current research.

2.4 Chapter Summary

The current chapter has provided a review of literature that is pertinent to the dissertation. The main objective of the dissertation is to develop a unified framework that would allow transportation agencies to project the sustainability of future revenue sources as a function of changing socioeconomic demographics. The sustainability of a funding source is defined as the source's ability to generate revenue to meet projected investment needs. As such, the review of available literature included a detailed look at the current state of transportation funding in America covering funding needs, revenue, and expenditures. It also provided background on the methodologies available to assess current system use and forecast system use in the future, as both are prerequisites to a transportation funding sustainability study.

CHAPTER 3. ASSESSMENT OF SYSTEM USAGE

3.1 Introduction

User-based transportation funding structures require charging users based on the extent to which they use the system. Thus, a reliable assessment of system usage is a prerequisite to any study that seeks to investigate the sustainability of transportation funding sources. In the context of this dissertation, highway system usage is expressed in terms of the vehicle miles traveled (VMT).

The current chapter discusses the traffic data that are used to quantify the current usage (VMT) of each road functional class by each of the 13 FHWA vehicle classes. These values are then summed for each census tract to provide an assessment of the relative traffic demand. The census tract VMT is a prerequisite of the subsequent spatial econometric models.

Subsequent chapters of this dissertation use this travel data in conjunction with social and economic data to identify the factors that influence travel, and therefore revenue. This chapter also assesses system usage by non-state residents; this is an important aspect of funding sustainability, as roadway use and consumption (and therefore, funding needs) are derived from usage by both residents and non-residents of the state. However, out-of-state vehicles do not contribute to certain funding sources, including registration fees.

3.1.1 An Overview of Traffic Volume

The source of traffic data includes 2012 AADT counts obtained from short-term traffic collection sites located at state highway segments and a sample of local (county and municipality) roadway segments. Data collected from long-term traffic count stations utilizing ATR and WIM technology were used to estimate location-specific and road functional class-specific vehicle class distributions.

In order to develop a comprehensive travel database for use in the subsequent estimation of travel funding, data on the following traffic characteristics were collected for each state road segment: location/district, route, starting milepost, ending milepost, AADT, truck AADT, road functional group, and national highway system (NHS) classification.

3.1.2 An Overview of Travel by Out-of-State Vehicles

Fuel consumption associated with travel on a state’s road network can be purchased in that state or in a surrounding state. For example, a commuter who lives and works in adjacent states will use both states’ roads but may choose to purchase fuel in only one of the two states. This means that this commuter contributes to infrastructure damage in both states, but contributes revenue to only one state. Historically, the assumption has been that these situations balance out—that is, for a given vehicle, the amount of fuel purchased in a state is roughly proportional to the amount of travel in that state

3.2 Methodology

3.2.1 Traffic Volume Distribution by Vehicle Class

The traffic volume for a FHWA vehicle class *i* for road segment *j* for road functional classification *k* can be calculated as follows:

$$AADT_{ijk} = (P_{ijk})(AADT_{jk}) \quad \text{3-1}$$

where: $AADT_{ijk}$ is the annual average daily traffic for FHWA vehicle class *i* for road segment *jk*, where *j* is the road segment and *k* is the road functional class; P_{ijk} is the percentage of FHWA vehicle class *i* in the traffic stream for road segment *jk*; and $AADT_{jk}$ is the annual average daily traffic for road segment *jk*. The VMT for a given FHWA vehicle class for a given road segment is defined as follows:

$$VMT_{ijk} = (AADT_{ijk})(L_{jk}) \quad \text{3-2}$$

where VMT_{ijk} is the vehicle miles traveled for FHWA vehicle class *i* for road segment *jk*, and L_{jk} is the length of road segment *jk* in centerline miles. The total VMT for FHWA vehicle class *i* for road functional class *k* is defined as follows:

$$VMT_{ik} \sum_{j=1}^{n} VMT_{ijk} \qquad 3\text{-}3$$

where VMT_{ik} is the VMT for vehicle class i for road functional class k. Conversely, if VMT_{ijk} is unknown for some road segments, an estimate for the total VMT for FHWA vehicle class i for road functional class k is defined as follows:

$$VMT_{ik} = (P_{ik})(L_k) \qquad 3\text{-}4$$

where P_{ik} is the average percentage of FHWA vehicle class i for road functional class k, and L_k is the total lane-miles of road functional class k. Short-term counts provide values for the total AADT and the truck AADT (vehicle classes 4 through 13), from which the AADT for small automobiles (vehicle classes 1 through 3) was calculated as follows:

$$AADT_A = AADT_{Total} - AADT_T \qquad 3\text{-}5$$

where $AADT_A$ is the AADT for vehicle classes 1 through 3, $AADT_{Total}$ is the total AADT, and $AADT_T$ is the AADT for vehicle classes 4 through 13.

3.2.2 Spatial Interpolation

To account for variance in travel data and to provide reliable network-level and census tract-level estimates of the percentage of out-of-state vehicles, Ordinary Kriging estimation was applied. This geostatistical spatial estimation methodology is just one of several distance-based algorithms that could help derive the percentage of each truck class. Kriging estimation, which accounts for the clustering of data collection sites observed in the long-term traffic count locations (refer to Figure 3.2), is accomplished using the distance and auto-correlation between data collection sites to impute unknown values into a random field.

3.2.2.1 Ordinary Kriging Assumptions

Ordinary Kriging, which is one of several Kriging estimation methodologies, is distinguished from the others in that it assumes that the mean is unknown but is constant over a small distances (termed the “local neighborhood”); the Simple Kriging assumes the mean is known and constant over all data points; and the Universal Kriging assumes the mean is the trend over small distances (Cressie, 1990 and 1993; Wackernagle, 1995).

Ordinary Kriging estimation assumes that data are omni-directional (i.e., only the distance between points is considered, not the direction (north, east, etc.)). Therefore, any trends that are a result of directional influences need to be removed first.

3.2.2.2 Ordinary Kriging Model Framework

Estimates of unknown values using Kriging are obtained from weighted linear combinations of known values defined as follows (Cressie, 1990, 1993; Wackernagle, 1995):

$$\hat{z} = \sum_{1}^{n} w_j v \tag{3-6}$$

where $\hat{z}$ is the predicted value, v is the known value, and w_j is the weight. In Ordinary Kriging, the value of v is unknown; therefore, a stationary random function $Z(x_i)$ is applied:

$$\hat{Z}(x_0) = \sum_{i=1}^{n} w_i(x_0)\, Z(x_i) \tag{3-7}$$

where $Z(x_i)$ is the value, x_0 is the location of the unobserved value, x_i is the location of the observed value, and w_i are the weights. The weights are a function of distance accounting for spatial clustering of data collection locations. The error is defined as follows:

$$\epsilon(x_0) = \hat{Z}(x_0) - Z(x_0) \tag{3-8}$$

To ensure the model is unbiased, the sum of the weights is set equal to one:

$$\sum_{i=1}^{n} w_i(x_0) = 1$$

3-9

We therefore seek to minimize the error variance:

$$minimize\ E[\epsilon(x_0)^2]$$

3-10

The covariance is defined as follows:

$$Cov\{x_j, x_i\} = E(\epsilon(x_i)\epsilon(x_j))$$

3-11

An assumption of intrinsic stationarity means the expected value between two points *h* distance apart is equal to zero:

$$E[Z(x+h) - Z(\text{x})]\text{=0}$$

3-12

The variance between two points *h* distance apart is defined as follows:

$$Var[Z(x+h) - Z(x)] = E[(Z(x+h) - Z(x))^2] = 2\gamma(h)$$

3-13

where $2\gamma(h)$ is the variogram.

3.2.2.2.1 Estimated Variogram

The variogram is the variance of the difference between points separated by the same Euclidean distance *h*. The exponential semi-variogram (variogram divided by two) used in the current research takes the following form (Cressie, 1990, 1993; Wackernagle, 1995):

$$\gamma(h) = C_0 + C_1(1 - exp\left(\frac{-3|h|}{a}\right) \tag{3-14}$$

where C_0 is the “nugget effect” (difference in sample values separated by extremely small distances), C_1 is the partial sill (difference between the nugget effect (C_0) and the maximum variogram value (sill)), and *a* is the range (the distance between two points at which the variogram no longer increases). The Matérn variogram takes the following form:

$$\gamma(h) = C_0 + C_1\left(1 - \frac{1}{2^{v-1}\Gamma(v)}\left(\frac{h}{a}\right)^v K_v\left(\frac{h}{a}\right)\right) \tag{3-15}$$

where K_v is the modified Bessel function of the second kind of the order *v*, Γ is the gamma function, and *v* is the smoothness parameter. It is important to note that the Matérn variogram is the same as the exponential variogram when the smoothness parameter (*v*) is 0.5 (Minasny and McBratney, 2005).

3.2.2.3 Mean Square Prediction Error

The mean squared prediction error (MSPE), a measure of goodness of fit, was calculated by sequentially removing one known data point at a time from the dataset, estimating the value of the removed data point, and then replacing the removed data point. The MSPE is defined as follows:

$$MSPE = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)}{n} \tag{3-16}$$

where Y_i is the actual value at location *i*, $\hat{Y}_i$ is the predicted value at location *i*, and *n* is the number of locations.

3.2.3 Sampling Procedure for Vehicles Registered Out-of-State

The methodology presented in this section was used to investigate the percentage of fuel sales attributable to vehicles registered outside of the state. The procedure for sampling fuel sales included: stratification, sample size determination, and data collection.

The analysis depended on the observed variance in the data and on a number of assumptions based on previous research, specifically, the assumption that the percentage of VMT attributed to vehicles registered outside of the state is 30%. Once the data collection is completed, the assumptions were reassessed to determine if further data collection was required. The percentage of fuel sold to out-of-state drivers was expected to be consistent at fuel stations with similar fuel sale volumes. The percentage is expected to be smaller for local stations with lower annual sales and larger for stations with high annual sales. Proper stratification and sampling locations were required to ensure that these factors were accounted for. If the collected data yields definitive spatial trends, then there is the opportunity to model the data using the Kriging methodology detailed in the previous section.

3.2.3.1 Stratification

Ideally, any sample drawn from a population must be adequately representative of the population. In this case, the population in question is the collection of all fuel sale transaction for a given year and the statistic of interest is the percentage of transactions to vehicles registered outside of the state. It was expected that the percentage of fuel sold to vehicles registered outside of the state would be consistent for stations with similar fuel sale volumes. However, determining the amount of fuel sold by stations proved impossible due to privacy issues. Therefore, an alternative approach was used in which the stations were stratified based on road functional class and rural/urban classification. The stratification groups were rural interstate, urban interstate, rural non-interstate, and urban non-interstate. The expectation was that the percentage of vehicles registered outside of the state and fuel sales would be higher at stations along interstates and at stations closer to the state border compared to those at non-interstates and far from state boarders. In addition, it was expected that urban and rural locations would also yield different results.

3.2.3.2 Sample Size

Once the strata were set, the next step was determination of the sample size. In this case, the sample was the required number of fuel purchase transactions that need to be sampled from each stratum. The sample size depended on the population size, the expected chance of the outcome, the confidence level, and the confidence interval.

The population is the total number of fuel sale transactions in each stratum. The expected chance of the outcome (in this case, the chance that the fuel was purchased by a vehicles registered outside of the state) was 30% based on previous research (Sinha, 1979). The confidence level is the measure of reliability of the result; the current methodology provided estimates for three separate confidence levels: 90%, 95%, and 99%. Lastly, the confidence interval is the range of values for which the estimate falls given the confidence level. For instance, a confidence level of 90% and a confidence interval of 5% would mean that 90% of the time the result will fall within plus or minus 5% of the estimated value. The formula to calculate the sample size for an infinite population is:

$$n = Z^2(p)(1-p) \qquad \text{3-17}$$

where *n* is the sample size, *Z* is the Z-score that corresponds to the given confidence level (for instance, Z = 1.645 for a 90% confidence level), and *p* is the probability of the expected outcome (in this case, p = 0.3). The calculated value for n can be corrected if the population is finite using the equation:

$$n_{finite} = {}^{n}\!\Big/_{1+\frac{n-1}{N}} \qquad \text{3-18}$$

where N is the population size. It may be noticed that for large populations (size greater than 100,000), n_{finite} reduces to n which is the case for the fuel purchase data. Table 3.1 provides the sample size required for 15 combinations of confidence level and confidence interval.

Table 3.1 Sensitivity of Fuel Transaction Sample Requirements to Confidence Level and Confidence Interval

	Confidence Level		
Confidence Interval (+/-)	90%	95%	99%
10%	57	81	139
5%	227	323	557
2%	1,421	2,017	3,484
1%	5,683	8,067	13,935
0.50%	22,731	32,269	55,741

3.3 Traffic Data Analysis for Indiana Case Study

The AADT data for highways in Indiana were obtained from the Indiana Department of Transportation (INDOT) Interactive Traffic Count Map (INDOT

2013a). The final analysis is conducted according to the NHS classification of roadways (NHS interstate, NHS non-interstate, and non-NHS, and local).

3.3.1 Roadway Classification

The NHS consists of all interstates, major arterials, and selected other routes that have been designated as important to the nation's economy, defense, and mobility (FHWA, 2013a). The NHS in Indiana is presented in Figure 3.1. The NHS system consists of several subsystems including: the Eisenhower Interstate System, other Principal Arterials, Strategic Highway Network (STRAHNET), major STRAHNET Connectors, and intermodal Connectors.

STRAHNET consists of the highways critical to the nation's strategic defense. Major STRAHNET connectors connect military installations with STRAHNET. The intermodal connectors connect the four subsystems and major intermodal hubs. The extent of the NHS system expanded greatly in 2012 as a result of the Moving Ahead for Progress in the 21st Century Act (MAP-21) classifying all principal arterials as NHS routes (FHWA, 2013b; OHPI, 2013a). Nationwide, nearly 60,000 route-miles were added to the NHS, increasing the existing NHS by 34%. Indiana saw greater-than-average expansion, from 2,902 route-miles pre-MAP-21 to the current 4,819 route-miles, an increase of 66% (Table 3.2).

Table 3.2 Updated NHS due to MAP-21 (FHWA, 2013b)

	Pre MAP-21 NHS	Non-NHS Principal Arterial System	Post MAP-21 NHS	Percent Increase
Indiana	2,902	1,917	4,819	66.1%
US Total	163,742	59,926	223,668	36.6%

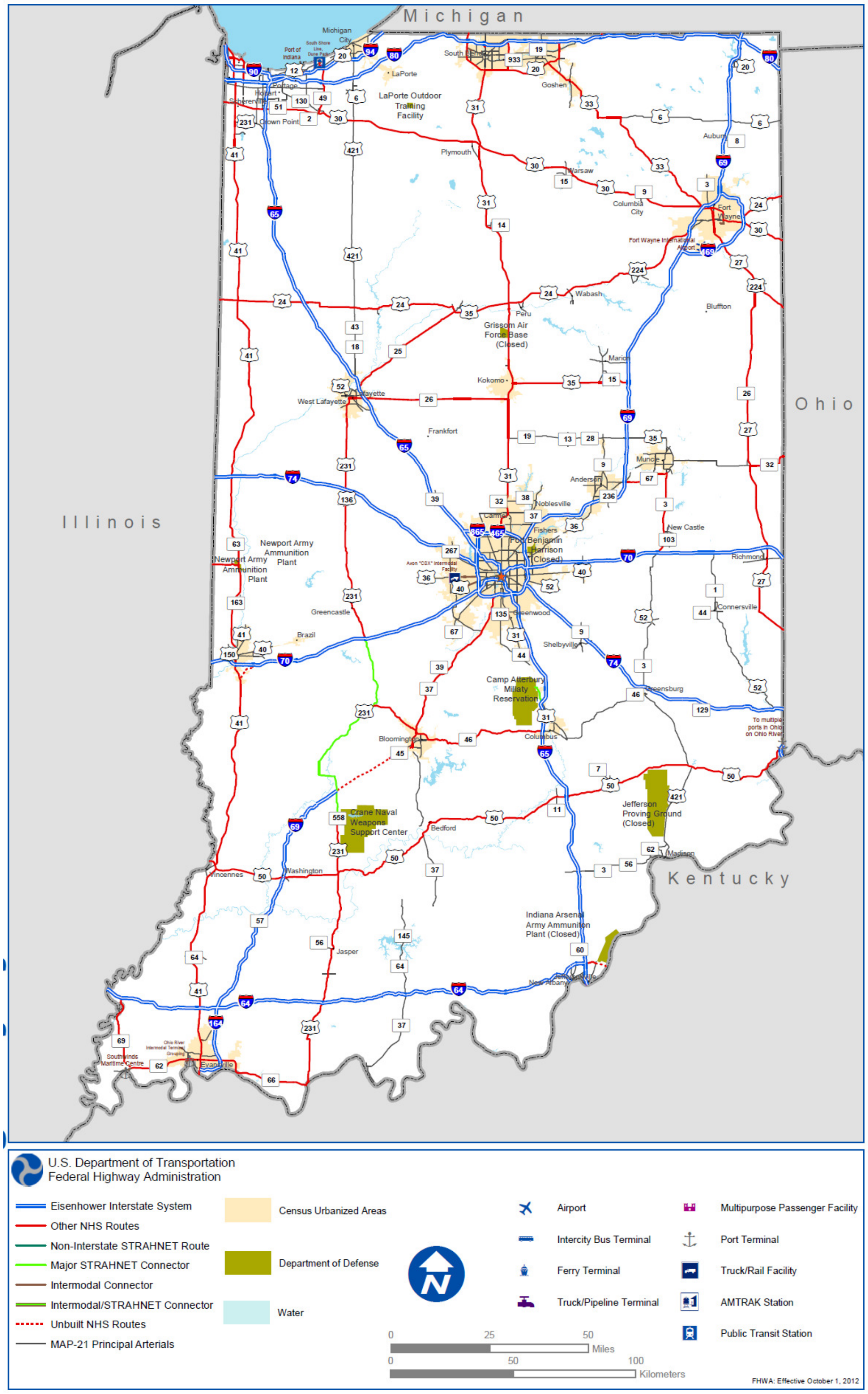


Figure 3.1 Indiana’s National Highway System (FHWA, 2013a)

3.3.2 Traffic Distribution

Traffic data are collected periodically at over 8,000 pavement segment locations in Indiana using short-term counts, while fewer than 100 segments were monitored using long-term counts. This means that for most segments only the total AADT and truck AADT are known. Long-term count stations collect data that are used to calculate traffic volume distributions (the percentage of each vehicle class in the traffic stream), which are then used to determine the VMT mix. The long-term count stations were spread out over four road functional classes; the majority of these are located in urban areas (as shown in Figure 3.2) and at interstates and principal arterials (as shown in Table 3.3).

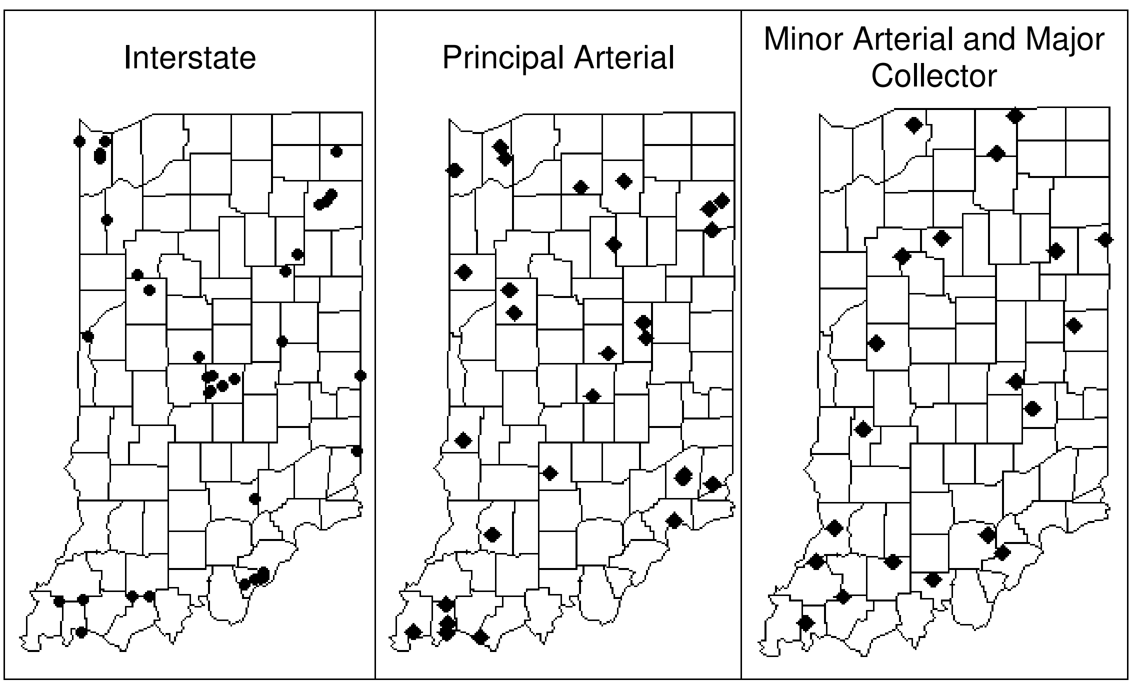


Figure 3.2 Spatial Distribution of Long-Term Traffic Count Stations

Table 3.3 Distribution of Long-Term Count Stations

Technology	Interstate	Other Principal Arterial	Minor Arterial	Major Collector	Total
ATR	16	16	5	13	50
WIM	18	13	1	1	33
Total	34	29	6	14	88

The clustering of count stations in urban areas may cause a skew in the average network-level estimates. The average percentage of each FHWA vehicle class for each road functional class obtained from the long-term traffic count stations (both WIM and ATR) is presented in Table 3.4. For the purpose of traffic volume distribution analysis, three road functional class groups were investigated: interstates, other principal arterials, and minor arterial and major collectors.

Table 3.4 Average Traffic Distribution by Vehicle Class at ATR and WIM Stations

FHWA Vehicle Class	Road Functional Class		
	Interstate	Principal Arterials	Minor Arterial / Major Collector
Class 1	0.40%	0.59%	0.57%
Class 2	57.71%	62.75%	62.82%
Class 3	19.63%	24.23%	27.05%
Class 4	0.33%	0.23%	0.08%
Class 5	3.69%	2.82%	1.51%
Class 6	0.60%	0.58%	1.13%
Class 7	0.10%	0.18%	0.39%
Class 8	1.12%	0.81%	0.69%
Class 9	15.44%	7.50%	5.59%
Class 10	0.18%	0.12%	0.10%
Class 11	0.55%	0.13%	0.02%
Class 12	0.21%	0.03%	0.01%
Class 13	0.05%	0.04%	0.03%

The variability associated with the mean values presented in Table 3.4 is presented in Figure 3.3. The spread between the maximum and minimum values for a given vehicle class can be as much as 50 percentage points. The inter-quartile range, the difference between the third quartile (Q3) and the first quartile (Q1), is as much as 24 percentage points. This variation justifies the need for additional analysis.

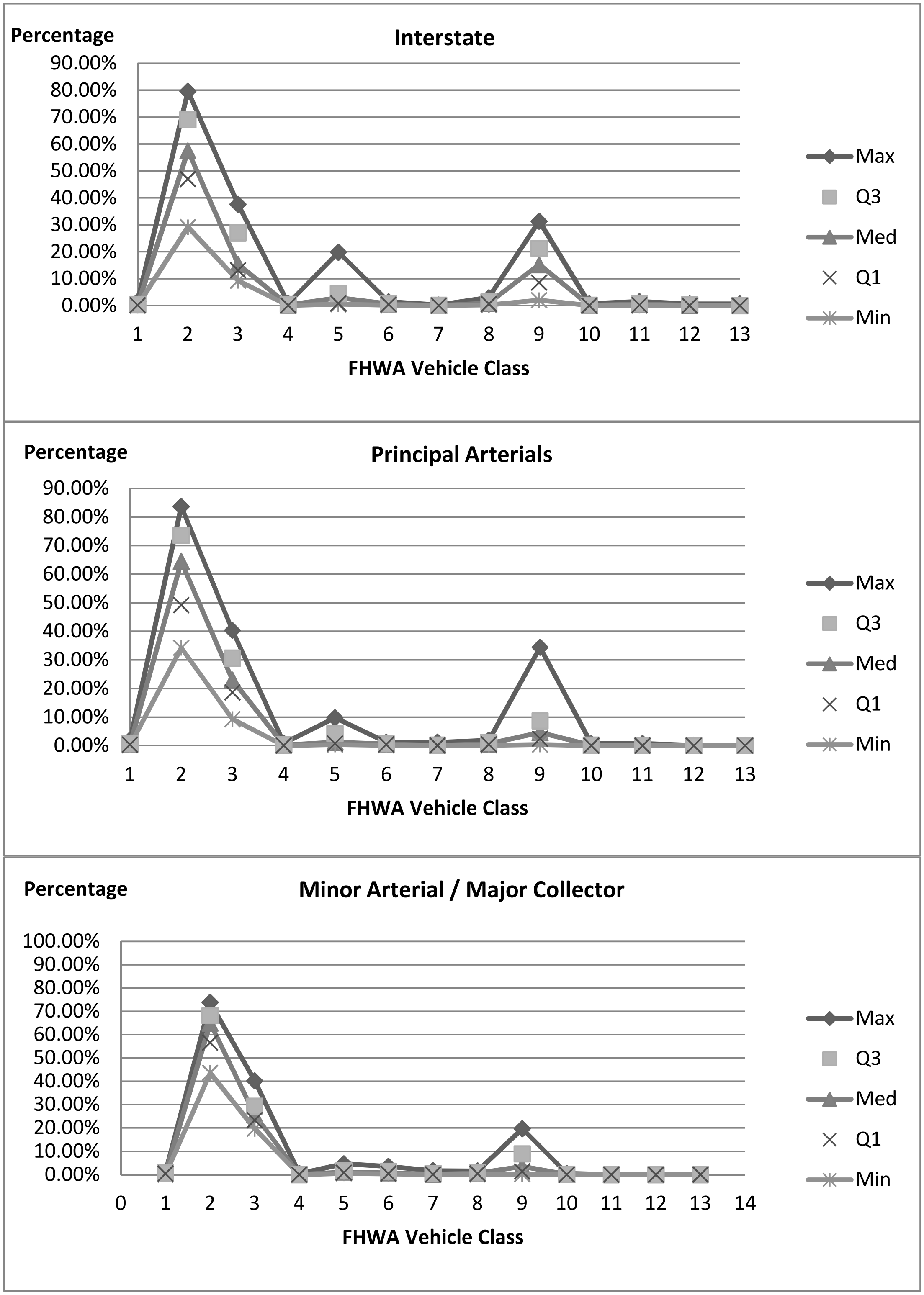


Figure 3.3 Variability Observed in Vehicle Class Distributions

3.3.3 Truck Traffic Distribution

The vehicle class distributions presented in the previous section experienced a significant amount of spatial variability. Additionally, the network-level averages based on permanent count stations were expected to cause bias in the results due to the imbalance between urban and rural data collection sites. Therefore, spatial interpolation is used to determine the percentage of class 9 (5 axle, two unit) trucks that are in the truck traffic stream.

3.3.3.1 Spatial Analysis Results

Kriging analysis was carried out with four combinations of estimators and covariance models for each of the three functional classes of roads (interstates, principal arterials, and minor arterials/major collectors). Weighted least squares (WLS) and maximum likelihood (ML) estimators were used and were each paired with the Matérn and exponential covariance models. The four resulting semi-variograms (variogram divided by two) are presented in Figure 3.4.

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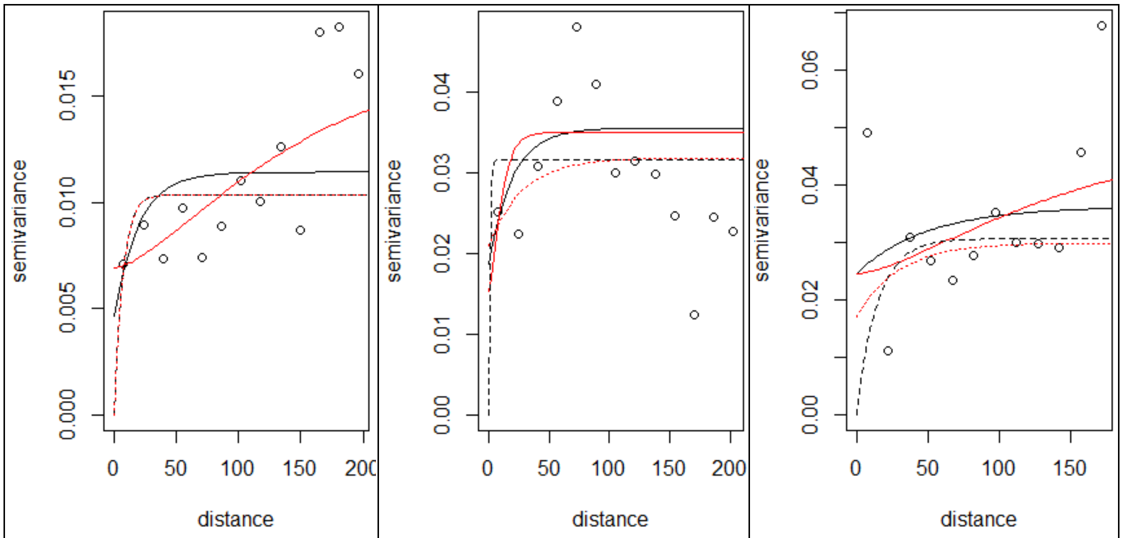


Figure 3.4 Semi-Variogram Functions

The specifications for the interstate, principal arterial, and minor arterial/major collector semi-variograms and their corresponding MSPEs are presented in Appendix B. The best estimator and covariance model for the three road functional classes were the ML estimator and exponential covariance model, the ML estimator and the Matérn covariance model, and the WLS estimator and exponential covariance model, for the interstate, principal arterial, and minor arterial /major collector, respectively.

The best combination of estimator and covariance models were used to estimate the percentage of class 9 trucks in the truck traffic stream for every road segment in Indiana reported to HPMS, including INDOT-owned and non-INDOT-owned segments. Additionally, statewide estimate maps were developed. These maps are presented in Figure 3.5 with the location of each data collection site and each state highway pavement segment location superimposed on the image (non-state highway segments were not included for the purpose of image clarity). The accompanying maps of the standard errors that arise during estimation are presented in the Appendix. It can be noticed how the standard errors increase for the estimation points farther from the known data collection sites.

Figure 3.5 shows that the estimate of class 9 trucks in the interstate truck traffic stream typically varies between 40% and 80%. The standard errors were consistently between 0.01 and 0.03, except across interstate 80/90 in northern Indiana, where the lack of WIM locations results in standard errors of 0.04. The percentage of class 9 for principal arterials was lower than the interstate estimates and varies between 30% and 75%. The standard errors were also greater than for interstates, ranging between 0.04 and 0.08, due to the higher variance in the data for that class of highways. The estimate of class 9 trucks for minor arterials and major collectors was lower than both interstates and principal arterials, and had standard errors similar to those of the principal arterials.

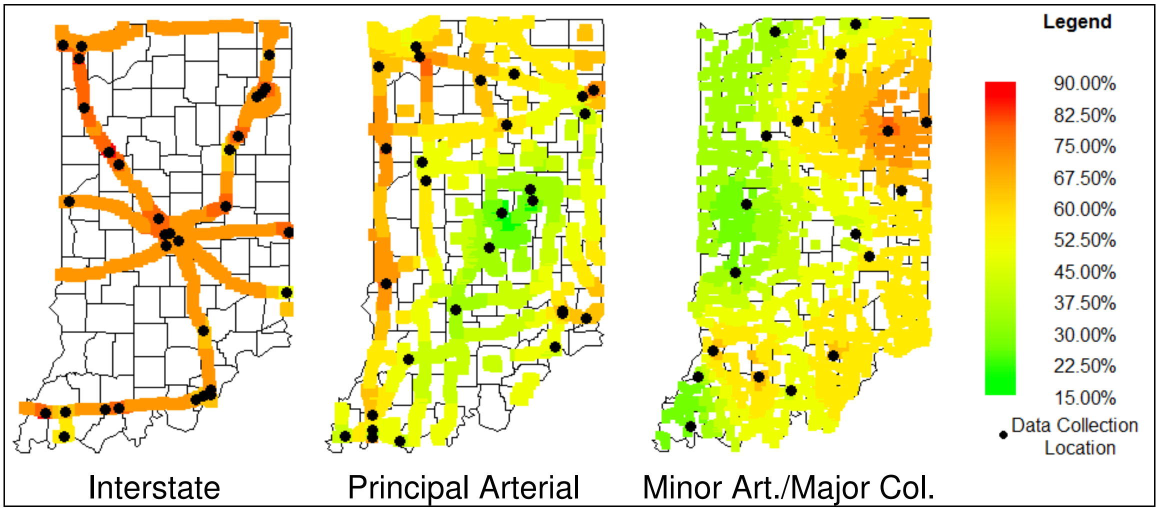


Figure 3.5 Estimated Percentage of Class 9 Trucks in the Truck Traffic Stream

3.3.3.2 Location-Specific Adjustments to Truck Volume Distributions

The Kriging analysis yielded road segment-specific estimates of the percentage of class 9 trucks in the truck traffic stream. The next step was to adjust the percentage of the other truck classes accordingly. Table 3.5 provides the average distributions of truck classes as a percentage of the total truck volume for interstates, principal arterials, and minor arterials/major collectors.

Table 3.5 Average Distribution of Truck Classes in the Truck Traffic Stream

FHWA Vehicle Class	Road Functional Class		
	Interstate	Principal Arterials	Minor Arterial / Major Collector
Class 4	1.48%	1.85%	0.84%
Class 5	16.57%	22.67%	15.81%
Class 6	2.69%	4.66%	11.83%
Class 7	0.45%	1.45%	4.08%
Class 8	5.03%	6.51%	7.23%
Class 9	69.33%	60.29%	58.53%
Class 10	0.81%	0.96%	1.05%
Class 11	2.47%	1.05%	0.21%
Class 12	0.94%	0.24%	0.10%
Class 13	0.22%	0.32%	0.31%
Total	100.00%	100.00%	100.00%

On average, class 9 trucks comprise approximately 70% of the truck traffic for interstates. If the estimate for the percentage of class 9 trucks for a given location is greater than the mean value, the other nine truck classes can be reduced according to their relative mean distribution. Conversely, if the estimate of class 9 trucks is less than the average value, the percentage of all other trucks classes can be increased according to the relative distribution. Examples of this adjustment are presented in Figure 3.6 and Figure 3.7 showing the distribution of truck traffic the percentage of class 9 trucks is greater than and less than the state average, respectively.

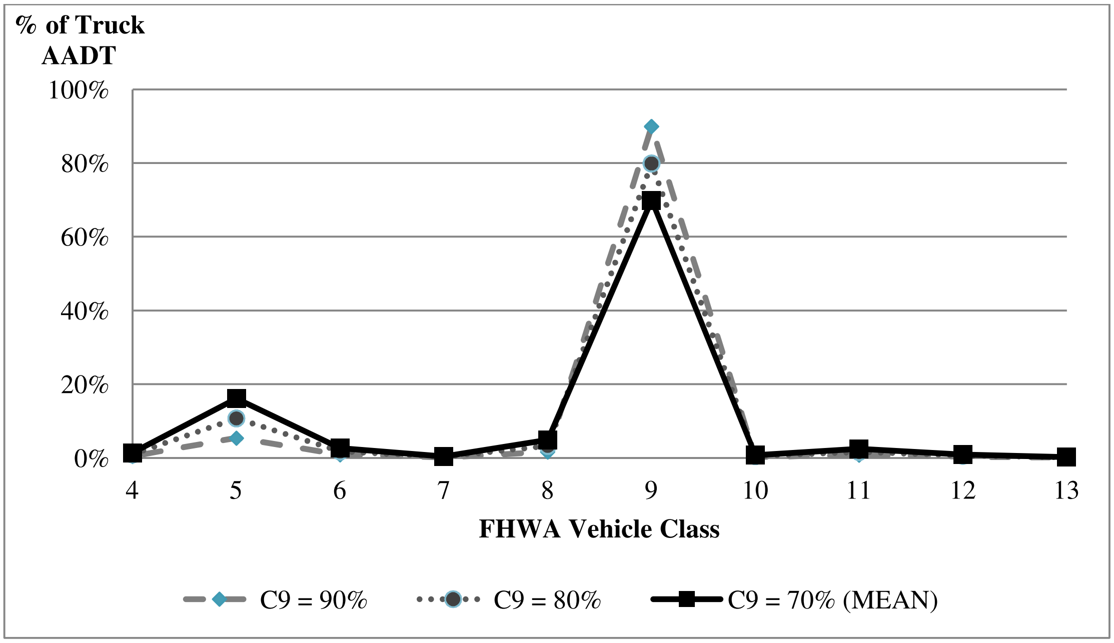


Figure 3.6 Distribution of Truck AADT When the Percentage of Class 9 (C9) Trucks Is Greater than the State Average

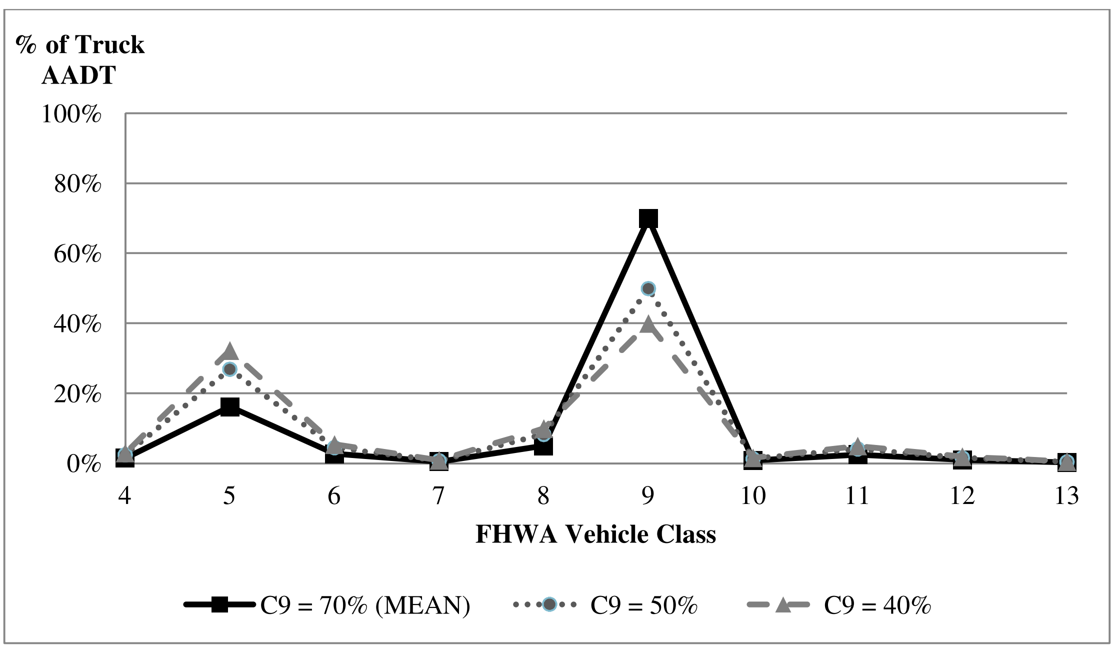


Figure 3.7 Distribution of Truck AADT When the Percentage of Class 9 (C9) Trucks Is Less than the State Average

3.3.4 VMT Results

The preceding sections detailed the process by which VMT can be calculated for state and local routes. The relative share of VMT for each census tract that can be attributed to travel along state highways routes compared local roads is presented in Figure 3.8.

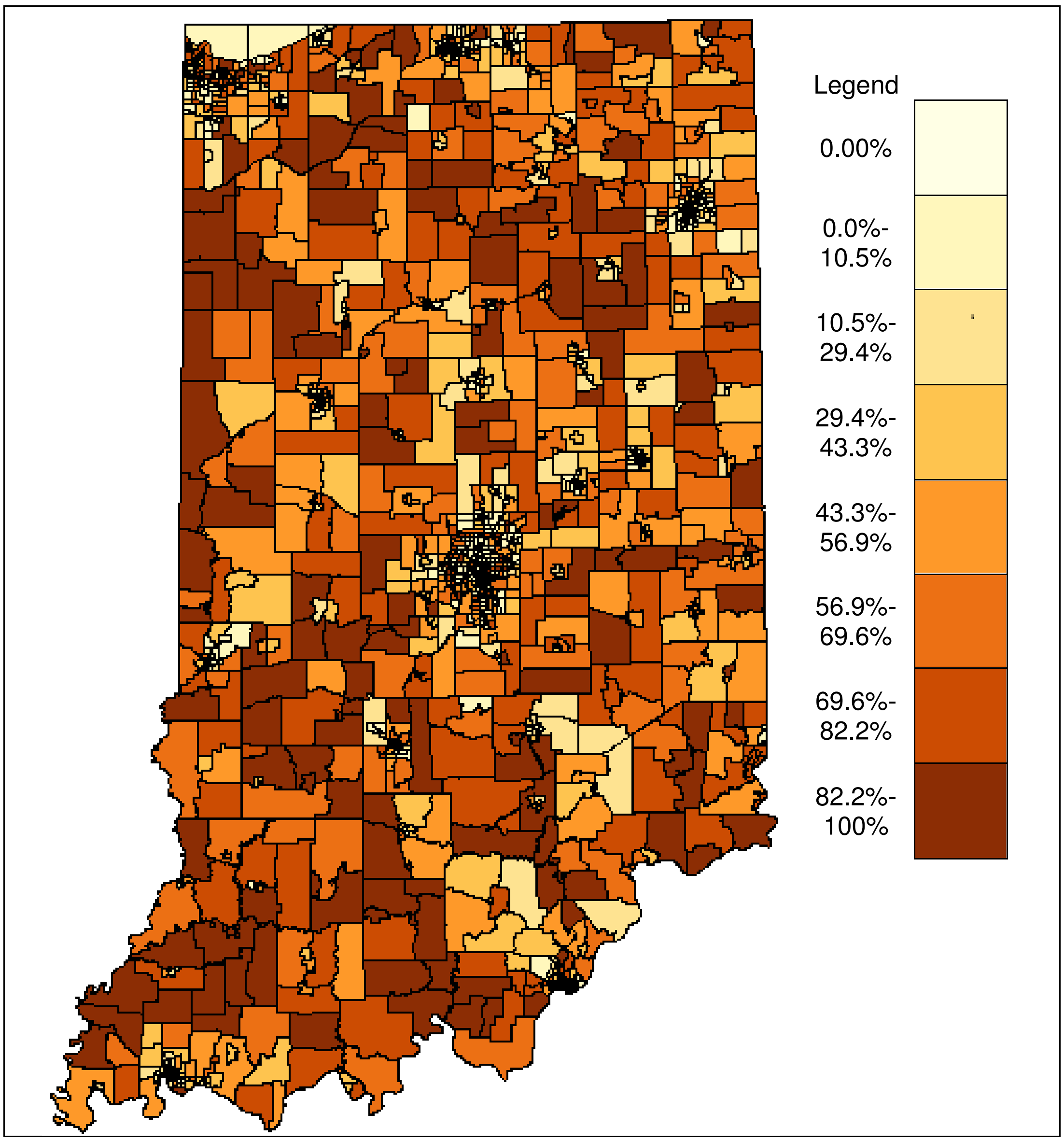


Figure 3.8 Percentage of VMT on State Highways

3.3.4.1 State Highway VMT

The results of the truck traffic stream composition were matched with each state-owned road segment ID. Equations 3-1 through 3-5 were then used to calculate the annual VMT for each of the 13 FHWA vehicle classes for each state-owned road segment for each year. The VMT for the individual road segments were summed to determine the total statewide VMT.

Prior to finalizing the annual VMT data, an adjustment was necessary to account for segments with missing data or duplicate data. This was accomplished by comparing the number of centerline miles with the data to the known number of centerline miles for each NHS classification. This process is illustrated in Table 3.6.

Table 3.6 Adjustment Factors for Annual VMT

NHS Class	Centerline miles (Calculated from AADT data)	Centerline miles (Actual)	Adjustment Factor (Calculated/Actual)
NHS Interstate (mainline)	1,012	1,014	1
NHS Non-Interstate (mainline)	2,910	3,000	0.97
Non-NHS (mainline)	7,113	6,932	1.03
Mainline Total	11,035	10,946	
NHS Interstate (ramp)	473	511	0.93
NHS Non-Interstate (ramp)	111	108	1.03
Non-NHS (ramp)	29	30	0.97
Ramps Total	613	649	

The adjustment factors were applied to the data to yield the finalized state-owned route annual VMT for 2012, which is summarized in Table 3.7.

Table 3.7 State-Owned Route Annual VMT by NHS Road Functional Class, 2012

Mainline or Ramps	NHS Class	Centerline miles	Annual VMT (billions)
Mainline	NHS-Interstate	1,014	15.68
Mainline	NHS-Non-Interstate	3,000	12.56
Mainline	Non-NHS	6,932	9.78
	Mainline Total	10,946	38.02
Ramps	NHS-Interstate	511	1.01
Ramps	NHS-Non-Interstate	108	0.11
Ramps	Non-NHS	30	0.03
	Ramps Total	649	1.15
Both	NHS-Interstate	1,525	16.69
Both	NHS-Non-Interstate	3,108	12.67
Both	Non-NHS	6,962	9.81
	State Owned Total	11,595	39.17

3.3.4.2 Local Roads

The process of determining VMT for State-owned routes relied on segment-specific traffic counts. However, at the local level, the percentage of road segments with AADT counts is limited, therefore, a different approach was needed. The limited number of route segments with AADT data for local roads was used as a sample to determine the average traffic stream composition. Next, the total VMT was back calculated from fuel sales data.

The back calculation of VMT from fuel sales data cannot yield segment-specific VMT and vehicle class distributions; however, it can provide a reliable estimate for the network-level VMT. In order to back-calculate the VMT for local routes, the amount of fuel sold (2.99 billion gallons and 1.20 billion gallons for gasoline and diesel, respectively), average fuel efficiencies (Table 3.8), and percentage of VMT by fuel type (Table 3.9) were needed (EIA, 2014a; EIA, 2014b; BTS, 2014).

Table 3.8 Average Fuel Efficiency by Vehicle Class, 2012

	FHWA Vehicle Class												
Year	1	2	3	4	5	6	7	8	9	10	11	12	13
Gasoline	42.50	23.20	17.10	7.20	9.42	6.33	6.33	5.36	5.36	5.36	5.36	5.36	5.36
Diesel	42.50	23.20	17.10	7.20	13.79	8.54	8.54	6.06	6.06	6.06	6.06	6.06	6.06

Table 3.9 Percentage of VMT by Fuel Type and Vehicle Class, 2012

	FHWA Vehicle Class												
Year	1	2	3	4	5	6	7	8	9	10	11	12	13
Gasoline	100%	99.5%	99.5%	5.0%	39.0%	19.0%	19.0%	19.0%	2.6%	2.6%	2.6%	2.6%	2.6%
Diesel	0.0%	0.5%	0.5%	95.0%	61.0%	81.0%	81.0%	81.0%	97.4%	97.4%	97.4%	97.4%	97.4%

These values were used to determine what percentage of the fuel purchased was consumed for travel on state routes, the remainder of which is assumed to have been consumed for travel on local routes. The calculation for the gasoline consumed on state routes is:

$$GC_{lmn} = (VMT_{lmn})(GE_{ln})(G_{ln}) \qquad 3\text{-}19$$

where GC_{lmn} is the gasoline consumed for travel on highway class *m*, by FHWA vehicle class *l*, in year *n*, VMT_{lmn} is the VMT, *GE* is the fuel efficiency for gasoline, and *G* is the percentage of vehicles that run on gasoline.

The calculation for the diesel consumed on state routes is:

$$DC_{lmn} = (VMT_{lmn})(DE_{ln})(1 - G_{ln}) \qquad 3\text{-}20$$

where DC_{lmn} is the diesel consumed for travel on NHS road class *m*, by FHWA vehicle class *l*, in year *n,* and *DE* is the fuel efficiency for diesel. The calculations for the gallons consumed on local routes are:

$$GC_{local,n} = TGC_n - \sum_{l}\sum_{m} GC_{lmn} \qquad 3\text{-}21$$

$$DC_{local,n} = TDC_n - \sum_{l}\sum_{m} GC_{lmn} \qquad 3\text{-}22$$

where $GC_{local,n}$ and $DC_{local,n}$ are the gallons of gasoline and diesel consumed for travel on local roads in year n and TGC and TDC is the total gasoline and diesel consumed in the state. These values are provided in Table 3.10.

Table 3.10 Fuel Consumption by NHS Road Functional Class, 2012

		Gallons Consumed (billions)	
State or Local	NHS Classification	Gasoline	Diesel
State	NHS-Interstate	0.67	0.47
State	NHS-Non-Interstate	0.55	0.19
State	Non-NHS	0.43	0.14
Local	-	1.24	0.54
	Total Gallons	2.89	1.34

There were a limited number of local road segments that had corresponding AADT data and geographic locations, which allowed the methodology introduced in Section 3.2.2 to be applied to a sample of local road segments. This methodology yielded a vehicle class distribution that was predominately automobiles as shown in Figure 3.9.

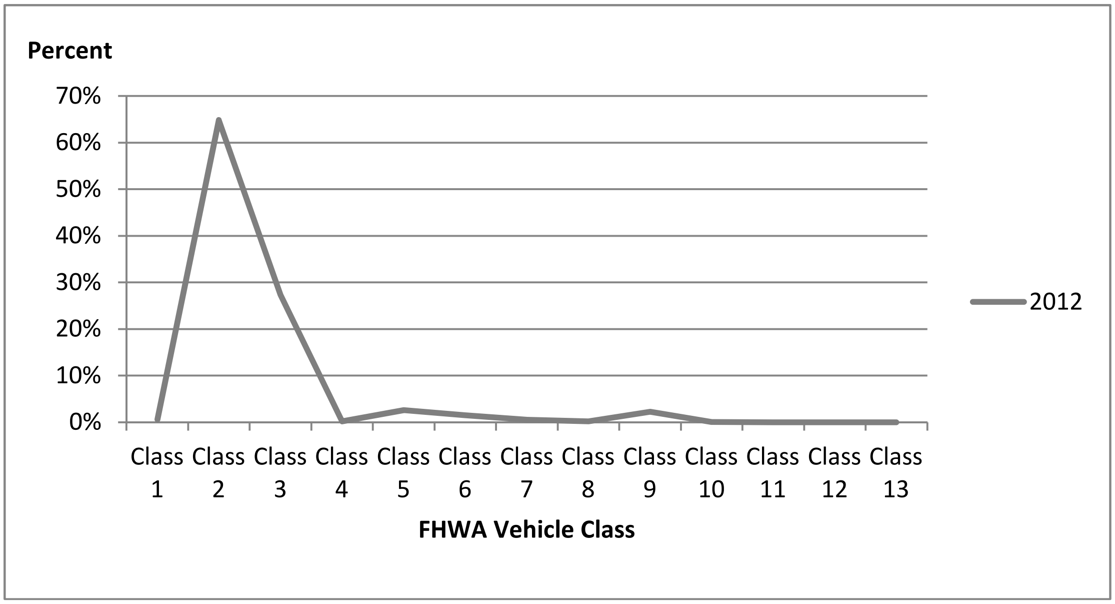


Figure 3.9 Average Vehicle Class Distributions for Local Roads

3.3.4.3 Summary of VMT Data

The final step is to calculate the local VMT for each year using the fuel consumption data and local route vehicle distributions. The equation to calculate the local VMT is:

$$Total\ VMT_{local,n} = \left(GC_{local,n}\right)(WGE_n) + \left(DC_{local,n}\right)(WDE_n) \qquad 3\text{-}23$$

where WGE_n and WDE_n are the average gasoline and diesel fuel efficiencies, respectively, for year n (weighted by vehicle class distribution and percentage of vehicles that run on gasoline and diesel). A summary of these data is presented in Table 3.11.

Table 3.11 Annual VMT by NHS Road Functional Class, 2012

State/ Local	NHS Class	Centerline miles	Annual VMT (Billions)
State	NHS-Interstate	1,525	16.69
State	NHS-Non-Int.	3,108	12.67
State	Non-NHS	6,962	9.81
Local	-	84,848	32.07
	Total	96,443	71.24

3.3.5 Traffic Data Summary

Accurate assessments of road usage were needed for subsequent analysis of the factors that influence the extent of travel. To this end, this section covered the acquisition and analysis of statewide traffic data for Indiana. The report presented the types of traffic data collected in Indiana, including annual average daily traffic counts obtained from short-term count stations, vehicle class distributions obtained from ATRs and WIM detectors. The variance in the vehicle class distribution data was analyzed; and to address this variance, a methodology was presented to attribute the fewer than 100 ATR and WIM data locations to the over 8,000 pavement segments using a combination of average values and geostatisical spatial estimation. The results provided segment-specific vehicle class distribution estimates and therefore more accurate distributions of traffic volume for each vehicle class and for each road functional class.

3.4 Usage by Vehicles Registered Out-of-State

Travel on Indiana roadways can be attributed to both Indiana residents and out-of-state drivers. The ability of current and alternative state funding sources to collect revenue from out-of-state drivers is limited depending on the funding mechanism. For instance, vehicle registration is collected to help fund the construction, maintenance, preservation, and operation of Indiana's roads and bridges. However, Indiana has no jurisdiction to collect these fees from vehicles registered outside of the state. Additionally, out-of-state drivers who purchase fuel in Indiana are required to pay Indiana fuel tax, however; if these drivers chose to purchase fuel prior to entering Indiana then the state is unable to capture any revenue. Furthermore, if the state were to impose direct use charging (such as a VMT fee) outside of a national, unified system it could face serious difficulty enforcing and collecting the fee from non-Indiana residents. To aid in understanding this dynamic, this section details the fuel purchased and travel by vehicles registered outside of the state.

3.4.1 Data Collection

The percentage of fuel sold to vehicles registered outside of the state was determined at each sampling location. This information can be acquired in two ways. First, there was the opportunity for corporate cooperation. The large fuel companies, such as Mobil or Shell, collect large amounts of data from their customers. The sources of these data are fuel sale loyalty cards, credit card receipts, and credit fraud protection records (many pay-at-the-pump locations require a driver to input the zip code associated with the credit card prior to fueling). This approach can yield large amounts of data, which would result in very accurate estimates. However, due to issues with consumer privacy and corporate competitiveness, corporate cooperation was not an option. Therefore, the chosen approach was to manually monitor each transaction to determine the amount of fuel sold and record the licenses plate of the vehicle.

3.4.1.1 Sampling

The total amount of fuel sold in Indiana in 2011 amounted to 2.93 billion gallons of gasoline, not including special fuels. The average amount of fuel purchased per transaction was 12 gallons; therefore, there were approximately 244 million fuel sales transactions in Indiana in 2011. Fifteen transactions per hour per station was a conservative estimate of the transaction rate, which was determined using the following equation:

$$T = \frac{TT}{N*OD*OH} \tag{3-24}$$

where *T* is the average number of fuel sale transactions per hour per station, *TT* is the total annual statewide transactions (244 million), *N* is the number of stations (2,738 (Census, 2007)), *OD* is the number of operating days per year (365), and *OH* is the average number of operating hours per day (18). Applying a transaction rate of 15 transactions per hour per station yielded the number of sampling hours required to obtain the required sample size. Table 3.12 presents the number of sampling hours.

Table 3.12 Sensitivity of Fuel Sampling Hours to Confidence Level and Confidence Interval

	Confidence Level		
Confidence Interval (+/-)	90%	95%	99%
10%	3.72	5.29	9.13
5%	14.90	21.15	36.53
2%	93.10	132.17	228.30
1%	372.40	528.67	913.20
0.50%	1,489.59	2,114.70	3,652.81

It is important to note that the above analysis assumes a homogenous population. Sampling locations in Indiana are not considered homogenous as a single population which is why the all stations in Indian were broken down into four strata. The population of stations within each strata are expected to be homogenous.

Based on the sample size requirements, it was determined that for each stratum, 25 fuel stations, spread randomly across the state, needed to be sampled for one-hour intervals. The locations of these stations are provided in Figure 3.10. At each sampling location, the type of each vehicle fueling during the one-hour period was recorded. The total number of transactions sampled is provided in Table 3.13. Each stratum met the sampling requirement of 323 samples to provide a confidence level of 95% with a confidence interval of 5%. Also, the number of gallons of gasoline purchased per transaction was recorded where possible.

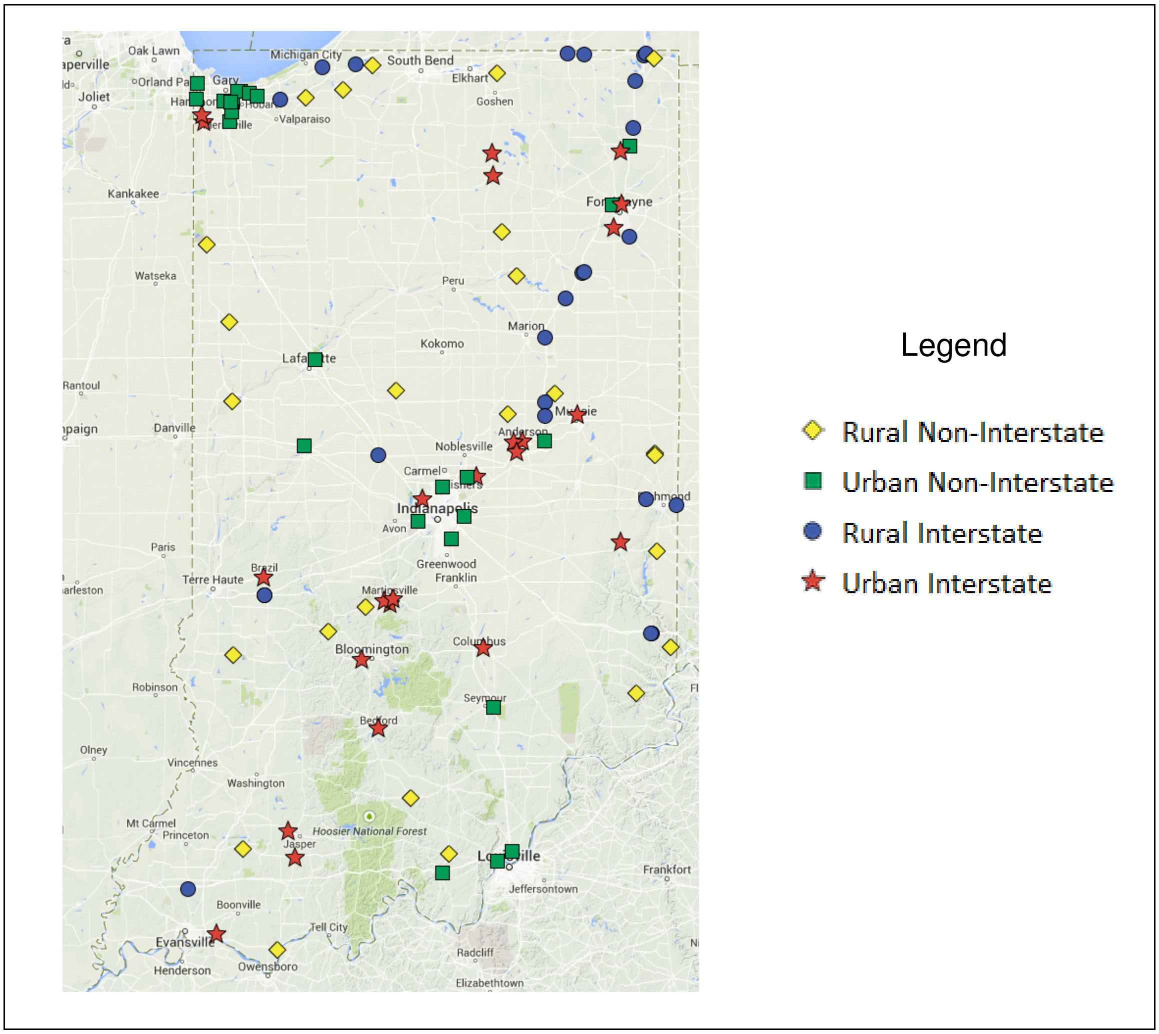


Figure 3.10 Sampling Locations for Fuel Data Collection

Table 3.13 Number of Transactions Sampled

		In State Count	Out of State Count	Missed Count	Total
Rural	Non Interstate	347	33	9	389
Rural	Interstate	258	130	14	402
Urban	Non Interstate	613	33	31	677
Urban	Interstate	514	131	28	673

3.4.2 Gasoline Sold to Non-Indiana Residents

The distribution of gasoline sales (Figure 3.14) is calculated as the product of the number of transactions per hour (Figure 3.12) and the average amount of fuel purchased (Figure 3.13).

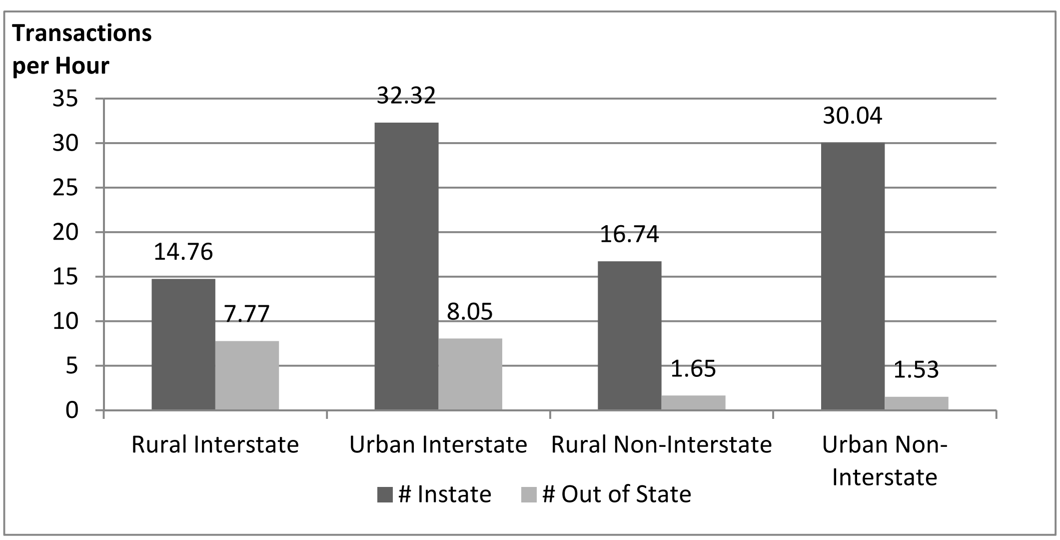


Figure 3.11 Gasoline Purchases Average Transaction Rates

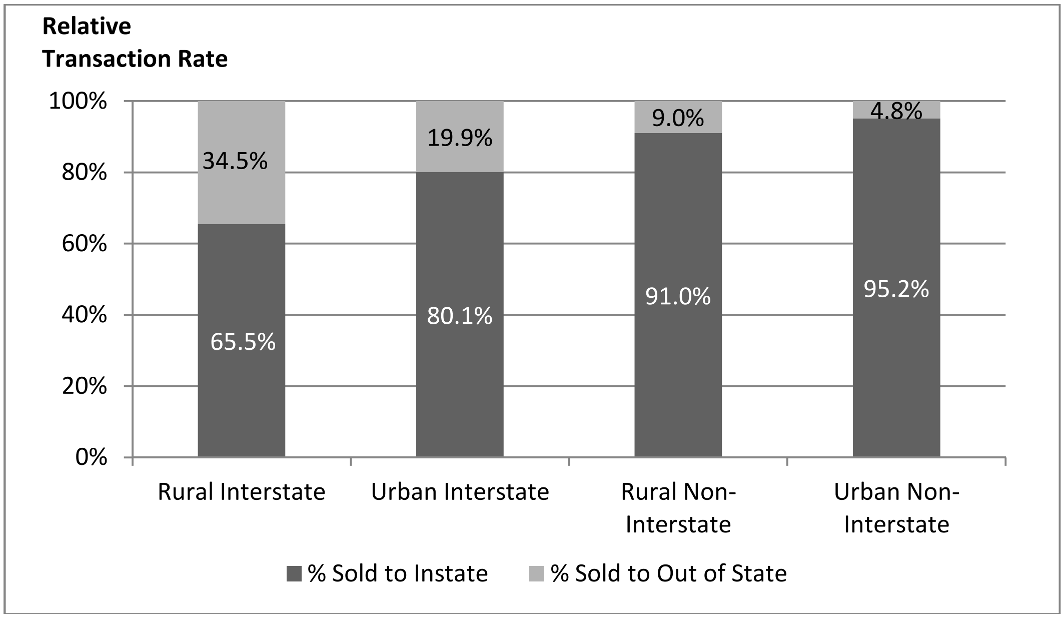


Figure 3.12 Gasoline Purchases Average Relative Transaction Rates

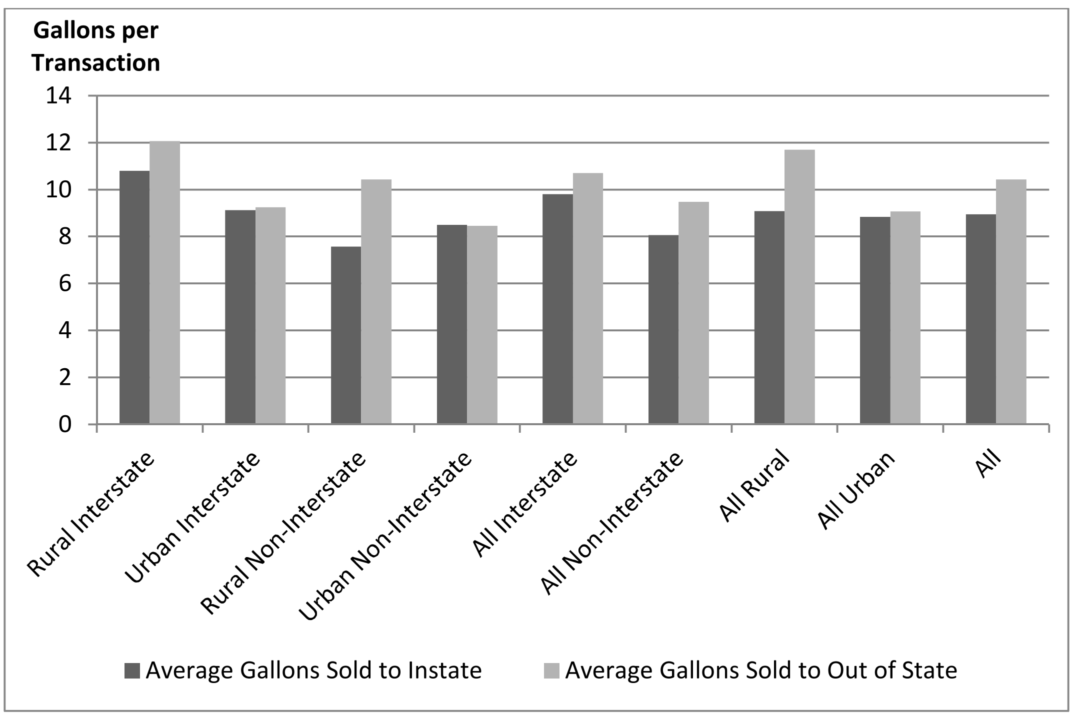


Figure 3.13 Average Amount of Gasoline Purchased per Transaction

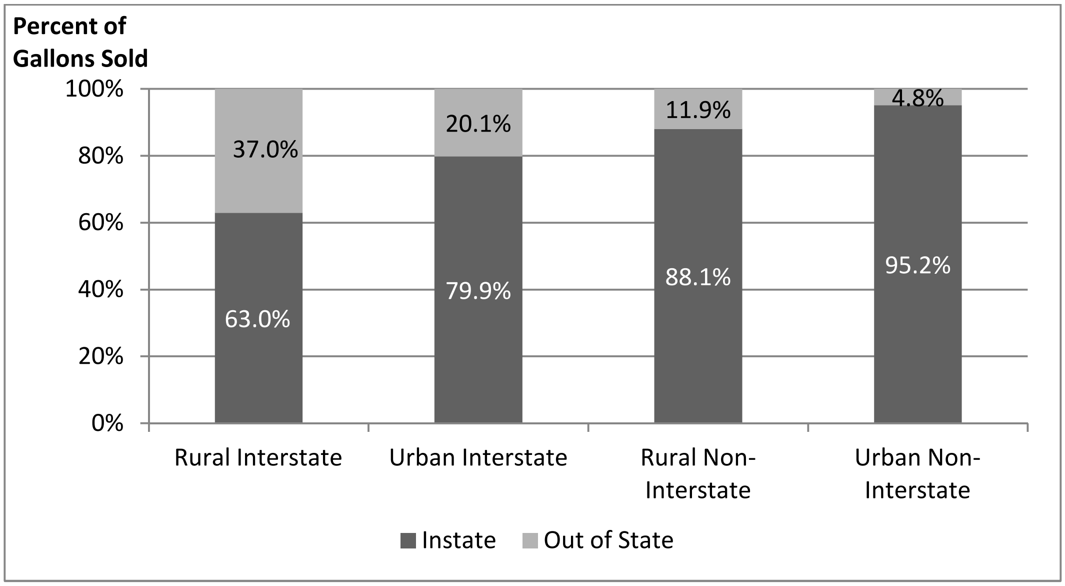


Figure 3.14 Average Distribution of Gasoline Sales at Sampling Locations

The results show that rural interstates experienced the greatest percentage of fuel purchased by vehicles registered outside of the state at 37.1% on average. This value decreased to 20.1%, 11.9%, and 4.8% for urban interstates, rural non-interstates, and urban non-interstates, respectively. There are approximately 2,700 gas stations in Indiana of which approximately 4.9%, 20.9%, 17.0% and 57.1% are classified as rural interstate, urban interstate, rural non-interstate, and urban non-interstate, respectively. Taking into account the distribution of fuel stations across the strata, Table 3.14 shows that estimate for the amount of gasoline sold to vehicles registered outside of the state is 10.83%.

Table 3.14 Estimate of Gasoline Sold to Vehicles Registered Outside of Indiana

Stratum	% of Gasoline Sold at Sampling Locations		Distribution of All Fuel Station Locations	% of Gasoline Sold at All Fuel Stations in Indiana	
	In-State	Out-of-State		In-State	Out-of-State
Rural Interstate	62.95%	37.05%	4.93%	3.10%	1.83%
Urban Interstate	79.86%	20.14%	20.94%	16.72%	4.22%
Rural Non-Interstate	88.07%	11.93%	17.00%	14.97%	2.03%
Urban Non-Interstate	95.18%	4.82%	57.14%	54.39%	2.76%
		Total	100.00%	89.17%	10.83%

3.4.3 VMT by Non-Indiana Residents

The amount of fuel purchased was used to estimate the travel made on Indiana roadways by vehicles registered outside of the state. The percentage of gasoline sold to non-Indiana residents was calculated at each fuel collection location. This value was then weighted by the average gasoline fuel efficiencies of the given road functional classification to provide an assessment of the percentage of travel completed by out-of-state drivers at each data collection location. To obtain a reliable estimate at the state level, spatial analysis using Kriging estimation was carried out. This yielded segment-specific splits of in-state vs. out-of-state travel that could then be multiplied by the segment VMT to yield values for in-state and out-of-state VMT. These values were then summed over the entire state to yield travel splits for each of the highway functional classes.

The results are presented in Figure 3.15, with the specific route estimates presented in Figure 3.16 and Figure 3.17 (the standard errors are presented in Appendix C). The NHS routes saw the highest percentage of VMT by vehicles registered outside of the state with 21.09% and 9.85% for NHS interstate and non-interstates, respectively. The non-NHS state and local routes saw 8.55% and 7.20% out-of-state drivers, respectively. Table 3.15 shows how these values were then weighted according to the relative distribution of VMT across the highway functional classes. The results indicate that 11.12% of the VMT in Indiana was traveled by residents of other states, which is slightly more than estimated 10.83% of fuel sold to non-Indiana residents.

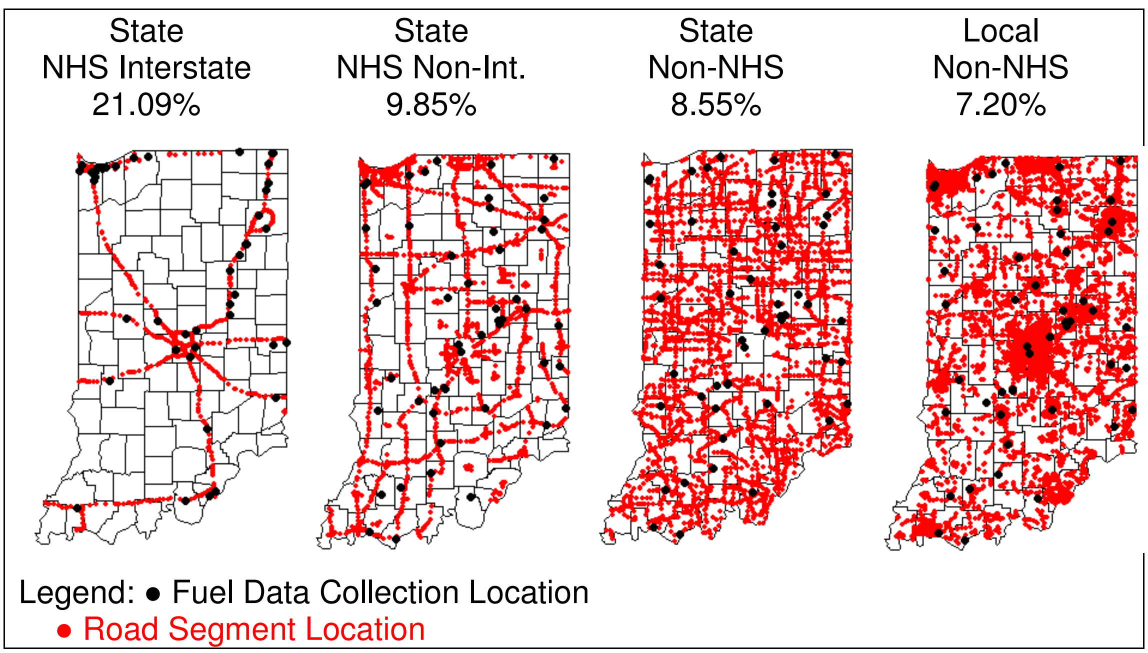


Figure 3.15 Percentage of Auto VMT by Non-Indiana Residents

Table 3.15 VMT by Out-of-State Gasoline Vehicles

State/ Local	NHS Class	All VMT	% Out-of-State
State	NHS-Interstate	23.43%	21.09%
State	NHS-Non-Interstate	17.78%	9.85%
State	Non-NHS	13.77%	8.55%
Local	-	45.02%	7.20%
	State	100.00%	11.12%

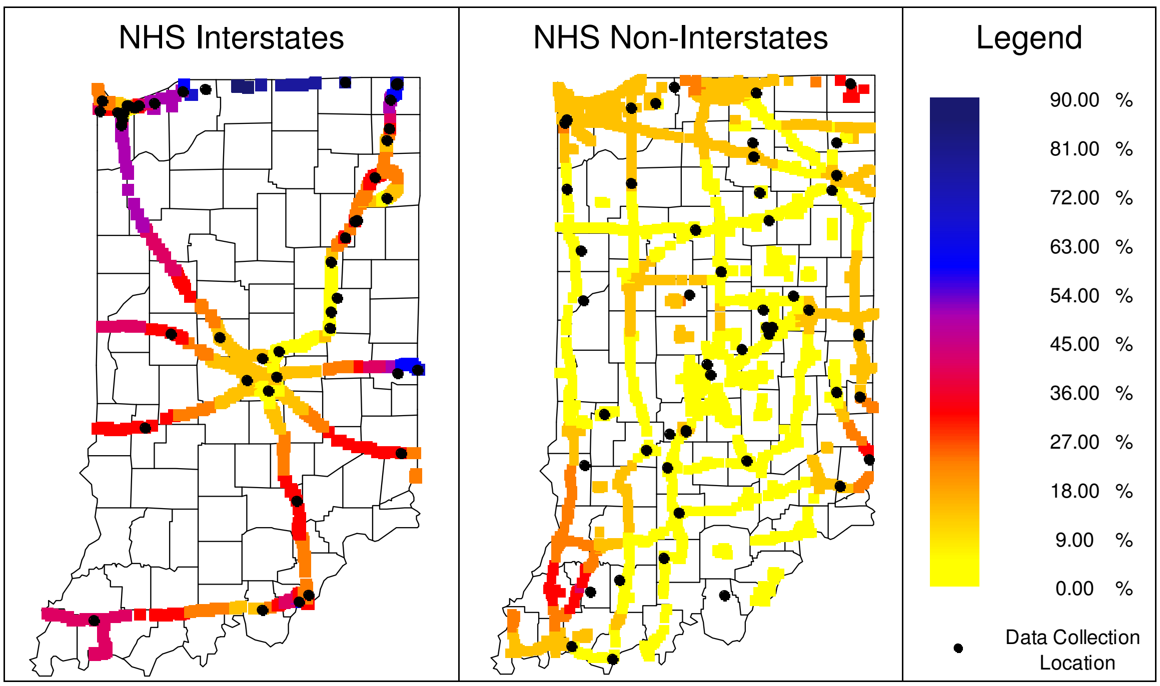


Figure 3.16 Percentage of VMT by Out-of-State Drivers on NHS (for gasoline)

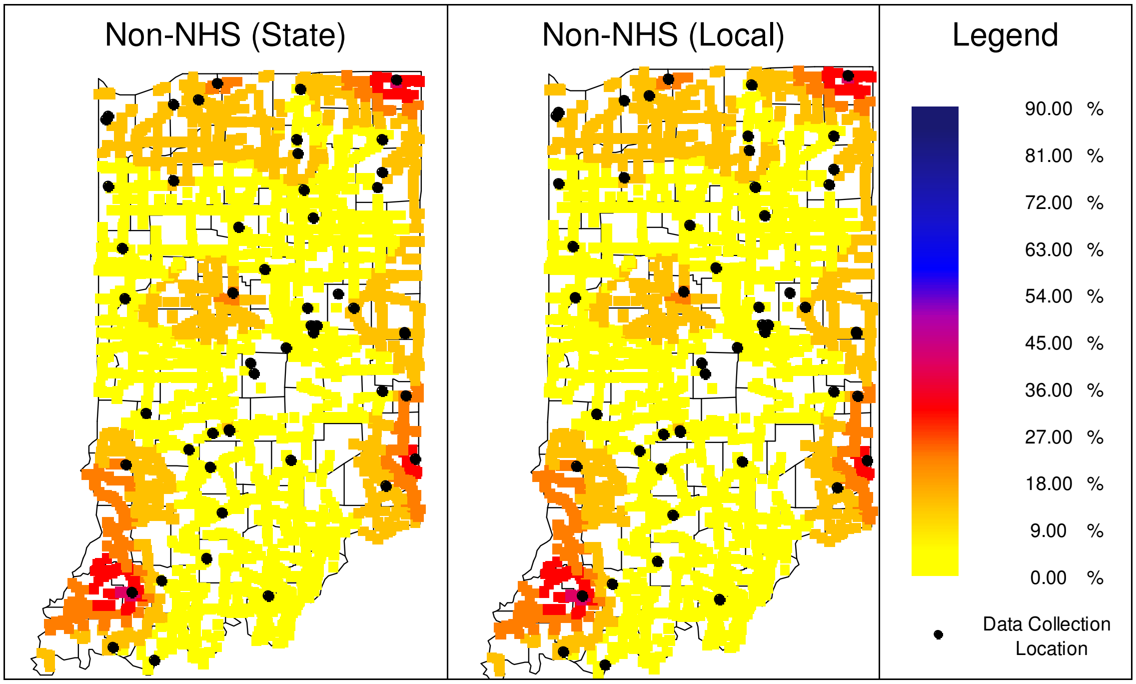


Figure 3.17 Percentage of VMT by Out-of-State Drivers on Non-NHS (for gasoline)

3.5 Chapter Summary

Chapter 3 detailed the process of acquiring and analyzing the traffic data that would be used in the subsequent analysis of social and economic factors that influence travel and therefore transportation funding. The study relied on a combination of segment-specific short-term traffic counts and spatial analysis of long-term permanent count stations. It was determined that the distribution of heavy trucks is not constant across state-owned routes. Class 9 trucks comprise the majority of the truck traffic, accounting for over 90% of the truck traffic for some locations along the interstates. Total VMT for local routes was back calculated from fuel sales data. Then, the local routes that had traffic data available were used as a sample to determine the vehicle class distribution. In addition, it was determined that 10.83% of the gasoline sold in Indiana was purchased by residents of other states. These out-of-state vehicles accounted for 11.13% of the total system usage in 2012.

CHAPTER 4. DESCRIPTION OF SOCIAL AND ECONOMIC DATA THAT INFLUENCES VEHICLE USE AND OWNERSHIP

This chapter analyzes a number of social and economic factors that are hypothesized to impact vehicle use and ownership. The analysis was carried out using Indiana as a case study state. The scope of the analysis included the state's 1,511 census tracts. These census tracts were chosen due to their relatively consistent population size (between 2,000 and 8,000) and the ability to receive high quality socioeconomic data from the United States Census Bureau (U.S. Census, 2014).

4.1 Population

Population may be the single, most influential underlying factor in predicting a region's transportation needs. Over the next 40 years, the population is expected to grow at a steady rate across the United States (U.S. Census, 2013).

In Indiana, it is expected that this population increase will be characterized by an increase in diversity, age, and density (INDOT, 2013c; U.S. Census, 2013; BRPTI, 2014). The current population density for Indiana is presented in Figure 4.1. Changes in a region's population can occur for one of two general reasons. First is a natural increase (decrease) due to new births and deaths (Figure 4.2), and the second is a change due to migration of individuals and families (Figure 4.3). The net effect of these changes is presented in Figure 4.4.

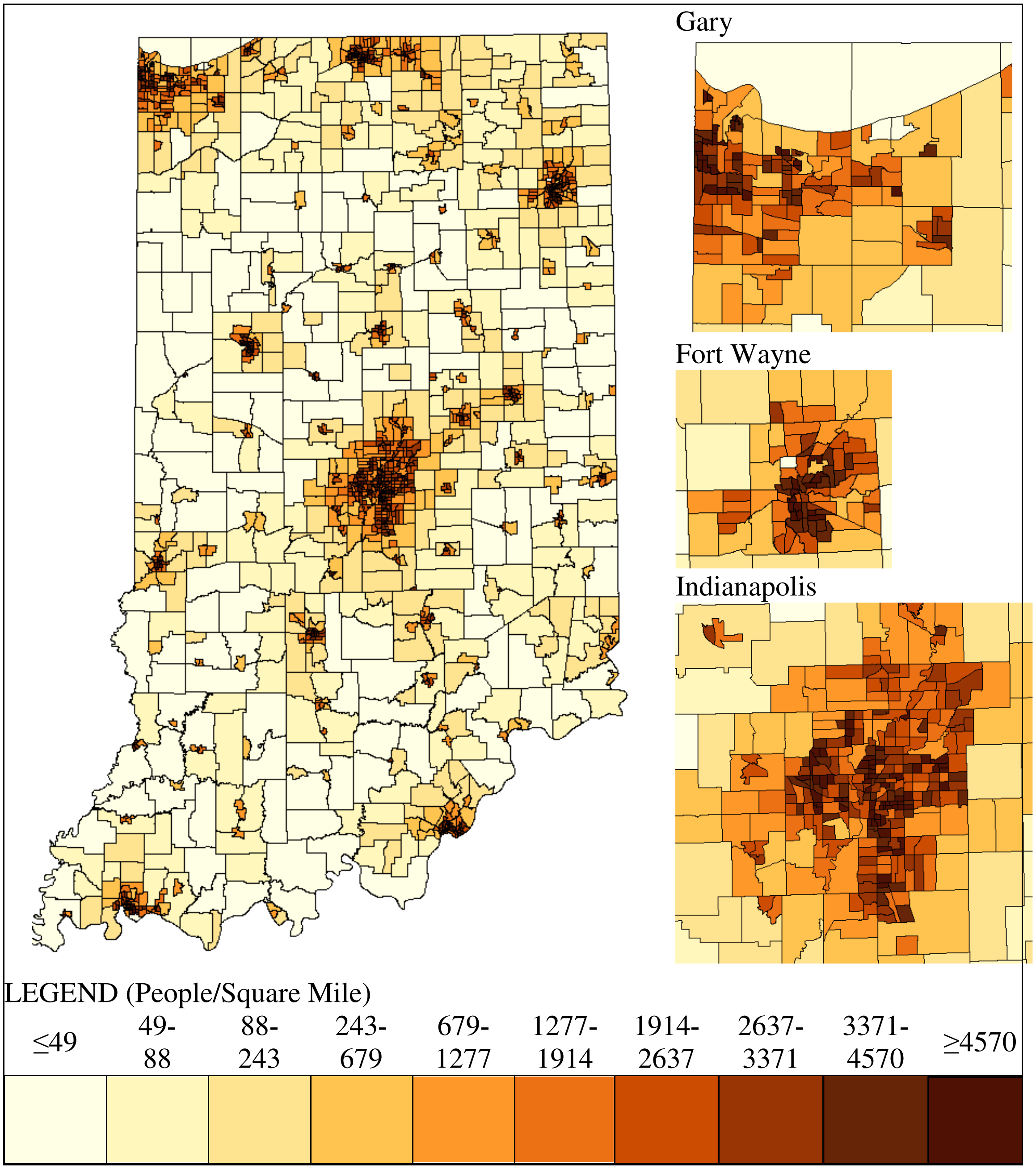
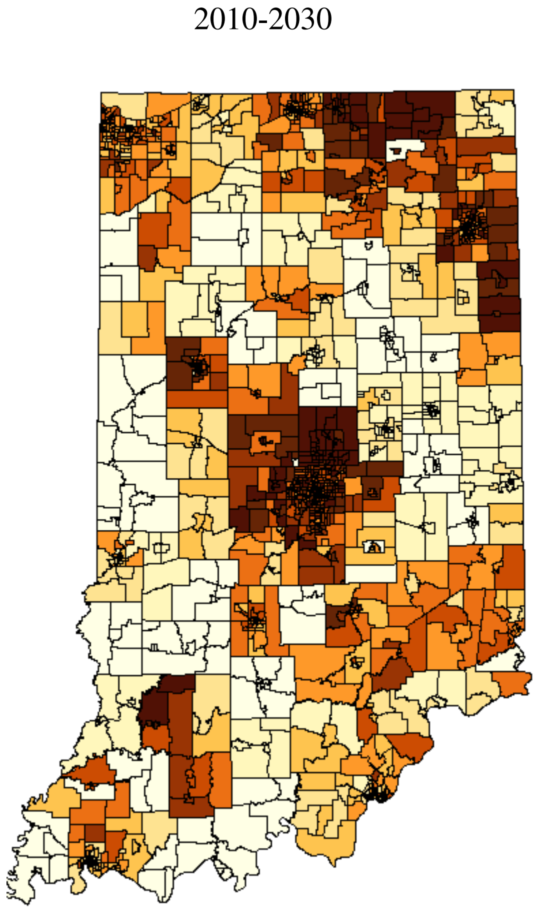


Figure 4.1 Population Density (People/Square Mile) Quantile Map



LEGEND
(Population Change 2010-2030)

-404-4	4-55	55-120	120-181	181-256
256-340	340-443	443-588	588-845	≥845

LEGEND
(Population Change 2030-2050)

-987 - -201	-201 - -115	-115 - -55	-55 - 7	7-86
86-153	153-266	266-435	435-675	≥675

Figure 4.2 Population Change due to Natural Causes Quantile Map

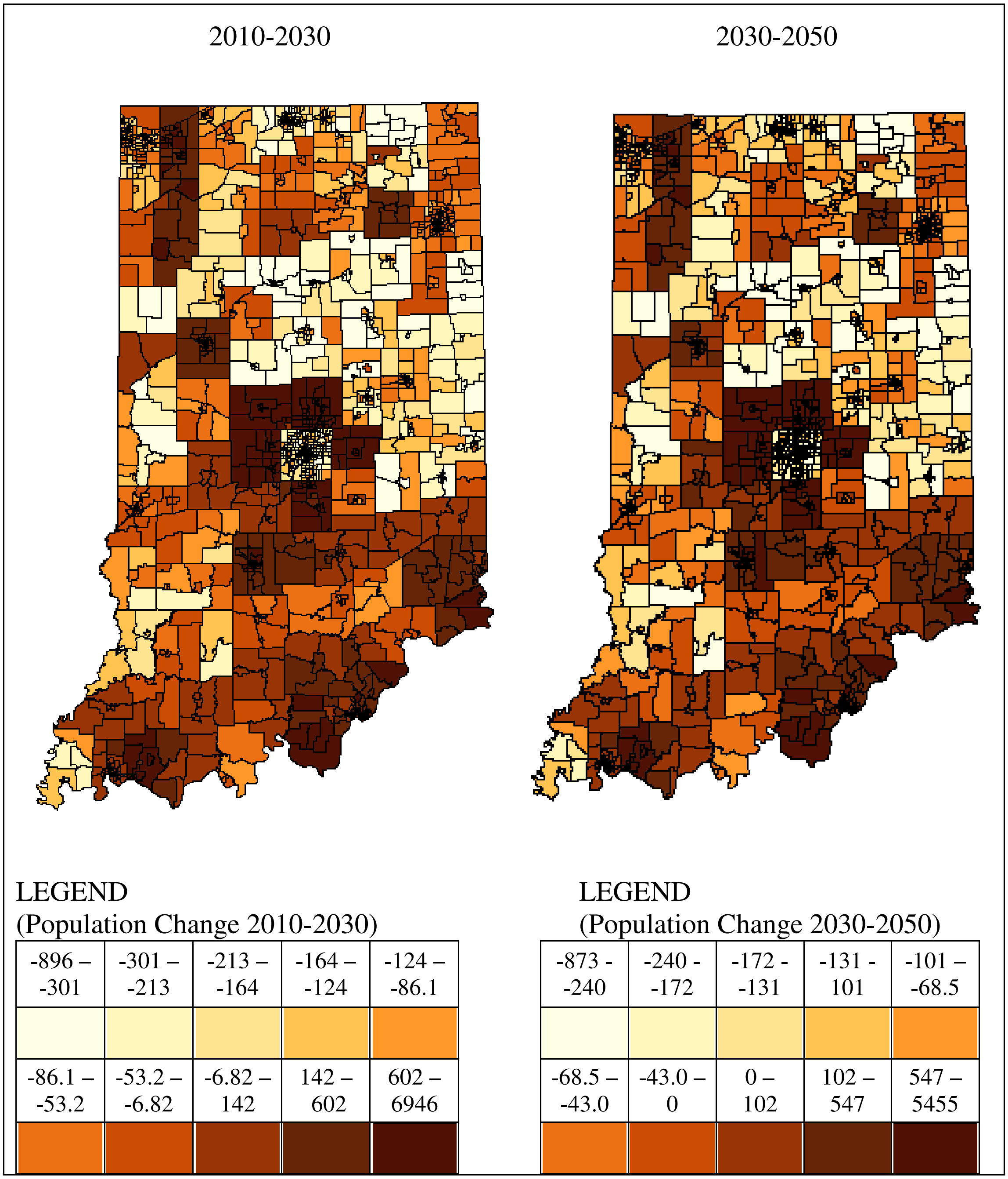
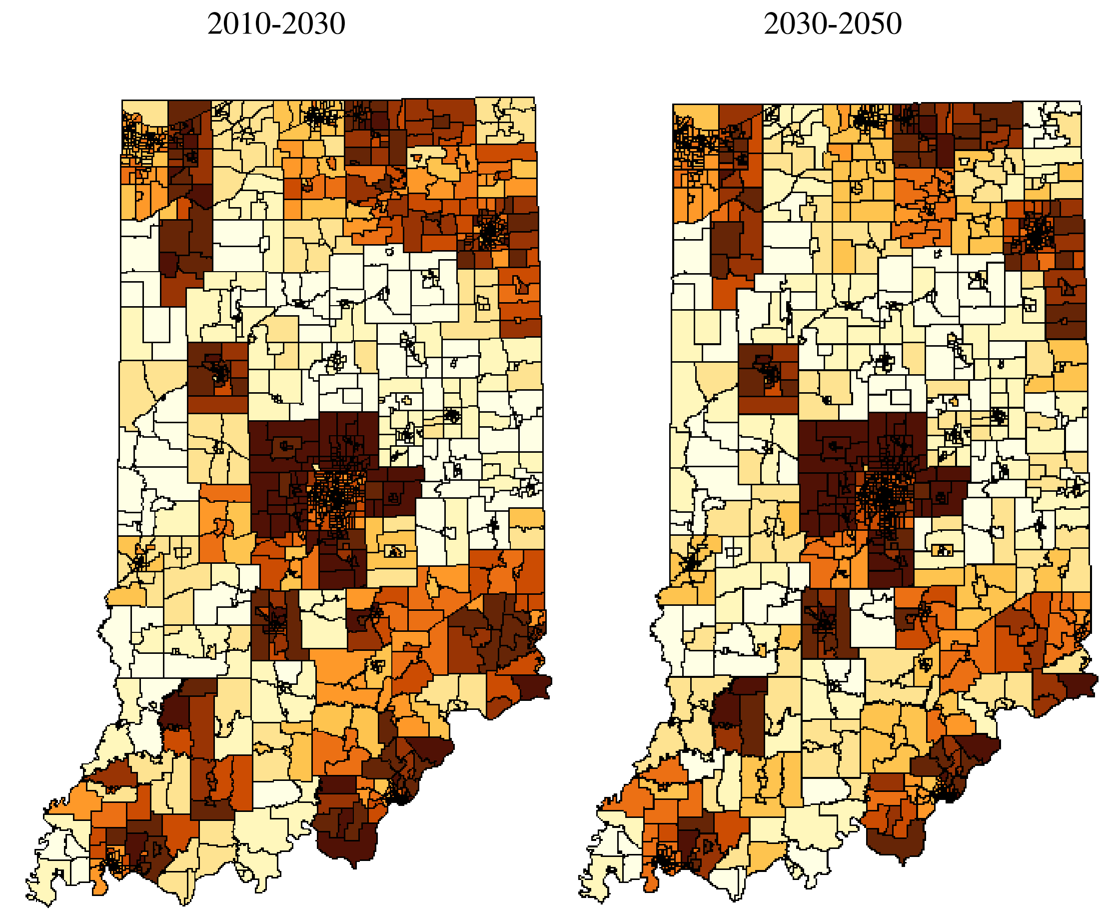


Figure 4.3 Population Change due to Migration Quantile Map



LEGEND
(Population Change 2010-2030)

-1080 – -165	-165 – -58.3	-58.3 – 67.9	67.9 – 144	144 – 229
229 – 324	324 – 439	439 – 615	615 – 1042	1042 – 10840

LEGEND
(Population Change 2030-2050)

-1681 – -285	-285 – -165	-165 – -89.0	-89.0 – 10.9	10.9 – 38.6
38.6 – 182	182 – 297	297 – 431	431 – 710	710 - 7585

Figure 4.4 Net Population Change Quantile Map

4.2 Education

As seen in Figure 4.5, the amount of education an individual receives can greatly influence earnings, disposal income, and unemployment. Therefore, it can be expected that education plays a significant role in determining the number of vehicles owned and the number of miles traveled.

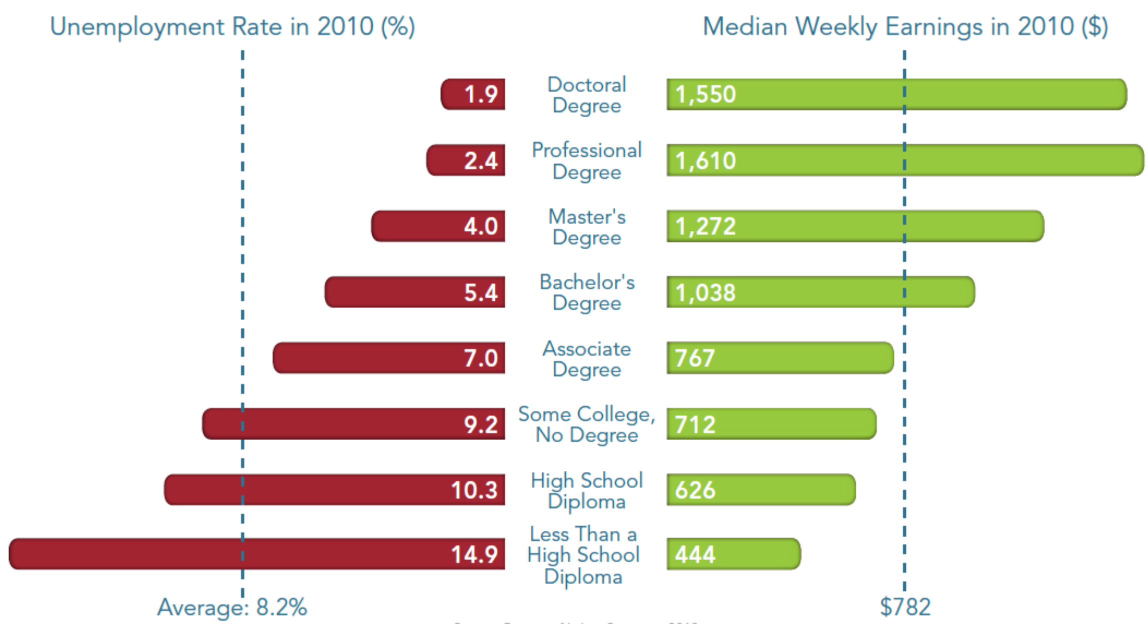


Figure 4.5 Education and Income (CHE, 2012)

In 2013, 23.8% of adults in Indiana had attained a bachelor’s degree or higher, which places it in the bottom half of all states (Table 4.1). However, as seen in Figure 4.6, this number sharply increases in urban areas, validating the belief that this percentage will increase in forthcoming years as Indiana sees an inter- and intra-state migration into urban areas (U.S. Census, 2013).

Table 4.1 Educational Attainment in 2013

	Bachelor's Degree or Higher
State: Minimum	18.90
1^{st} Quartile	26.18
State Average	29.30
3^{rd} Quartile	32.18
State: Maximum	55.10

In order to climb into the top 25% of bachelor degree attainment by 2050 (assuming all other state values are held constant), the percentage of adults holding a bachelor’s degree would have to grow at a rate of 1% annually. For Indiana to reach the highest state average observed today, this rate would have to increase to 2.2% annually. There are a number of legislative bodies working toward these goals. The Indiana commission for Higher Education (2012) has made it a goal to double the number of degrees being awarded and increase the attainment rate for all higher education to 60% by 2025.

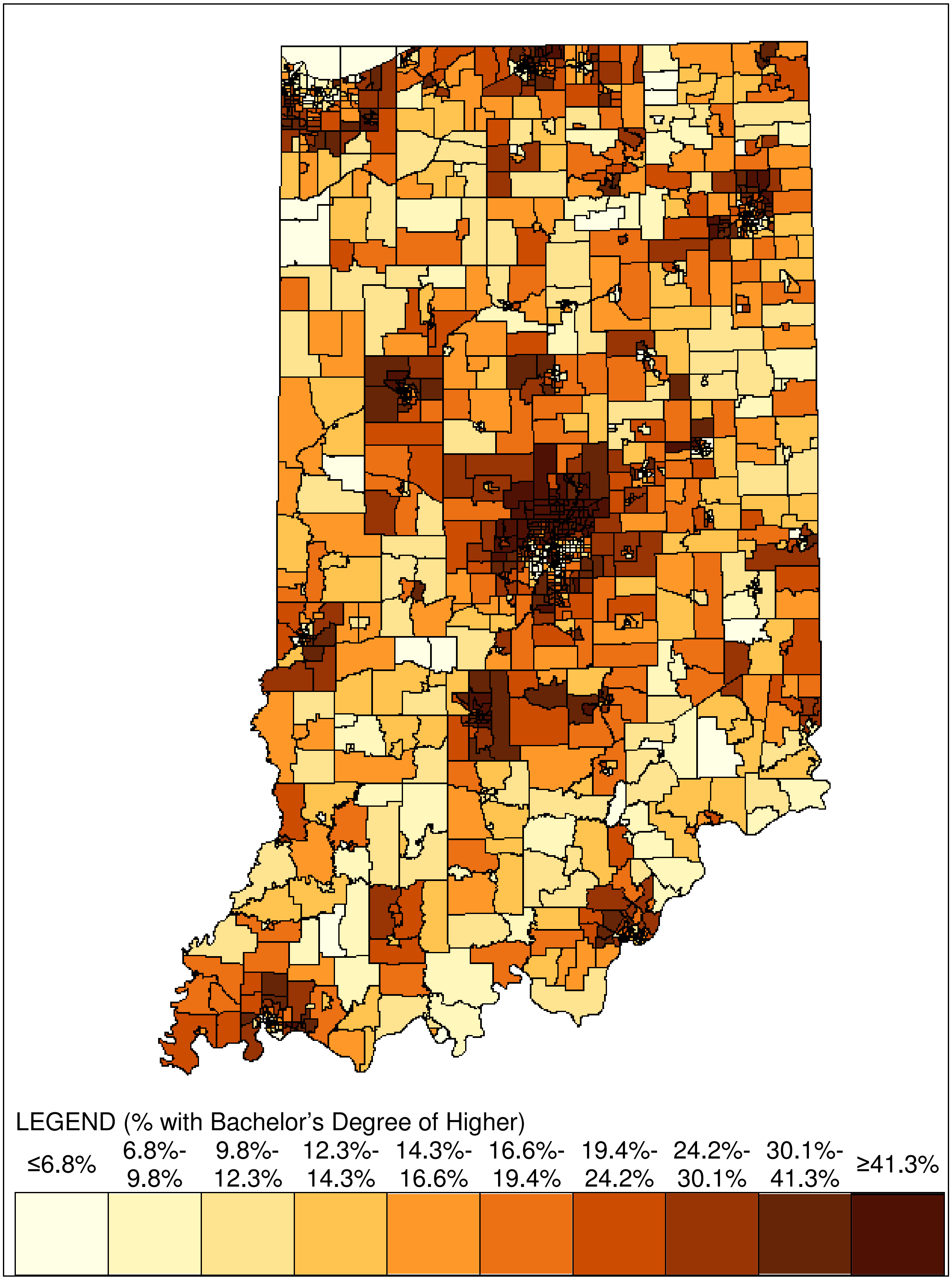


Figure 4.6 Education (Percentage with a Bachelor's Degree or Higher) Quantile Map

4.3 Unemployment

The unemployment rate for a given geographic region can impact passenger vehicle use and ownership. It has a direct effect in terms of the miles traveled as part of a daily commute and to a lesser extent, the miles traveled in search of work. Indirectly, a decrease in per capita ownership would be expected for areas with higher unemployment due to decreased disposable income (Melick, 2003).

Figure 4.7 shows the unemployment rate volatility in the US and Indiana (BLS, 2014). The sources of such vitality are extremely complex (Davis et. al., 2006) and outside the scope of this dissertation. Therefore, subsequent analysis will investigate the sensitivity of vehicle use and ownership to a change in the unemployment rate.

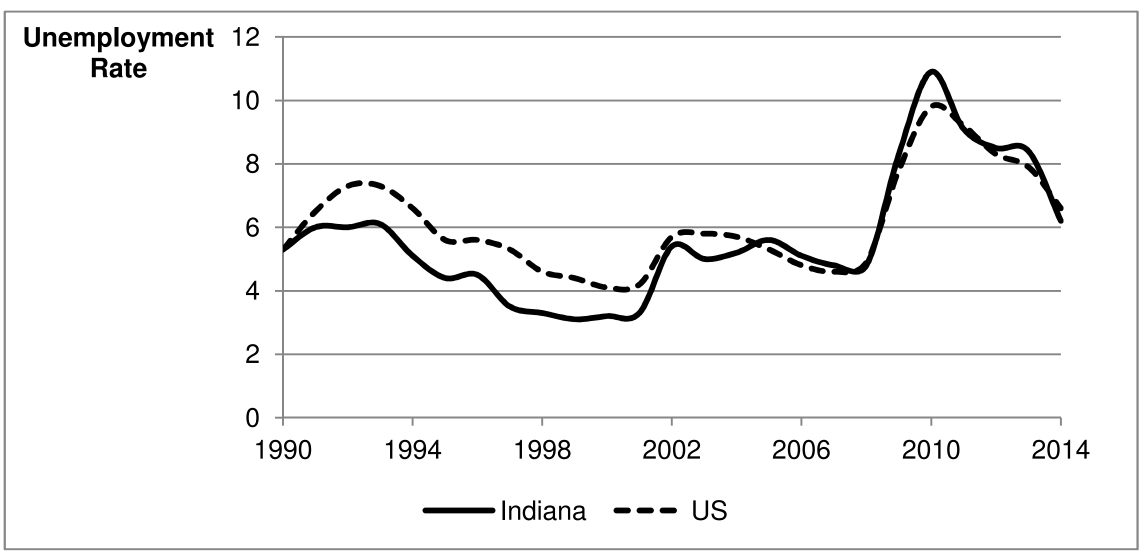


Figure 4.7 Historical Trend in the Unemployment Rate

4.4 Income

Across the US, a rise in per capita vehicle ownership has been attributed to a rise in per capita income (Dargay et. al., 2007). Higher per capita income is generally associated with lower use of public transit (Dargay, 2001).

The national trend is mirrored in Indiana (Figure 4.8), where the inflation adjusted per capita income rose steadily over the past 40 years (STATS, 2014). However, the per capita income growth in Indiana over the past decade has not kept up with the national rate.

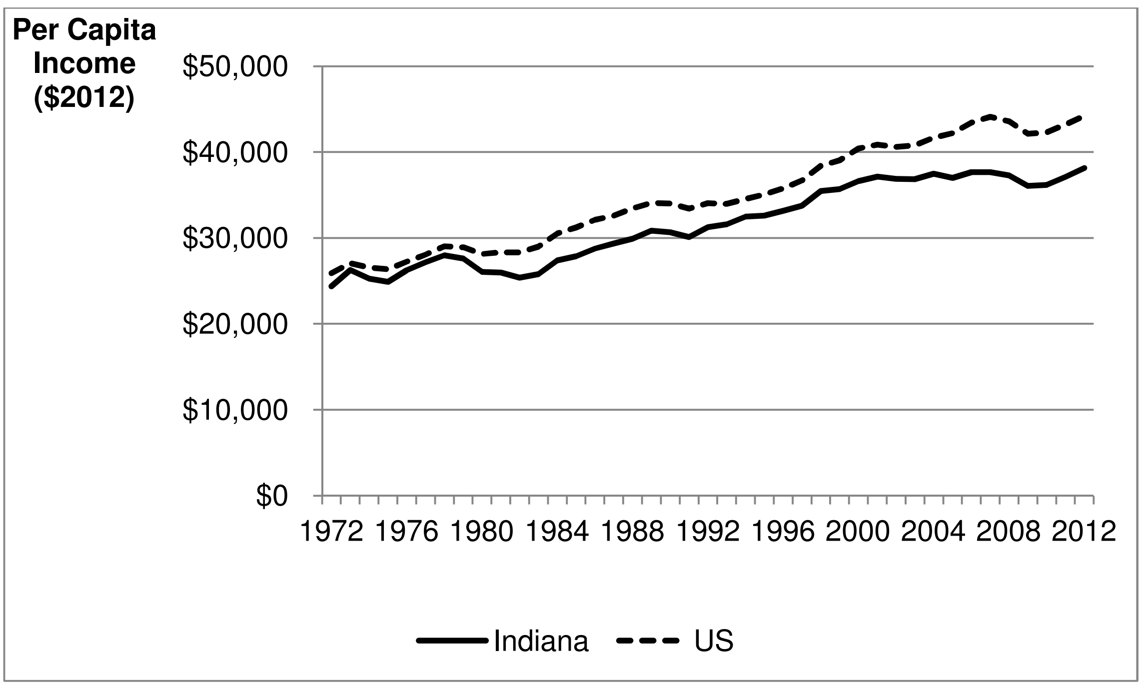


Figure 4.8 Per Capita Income Trends

4.5 Manufacturing

The industry mix in a region can influence the use and ownership of vehicles. It has been shown that in urban areas with a higher proportion of construction or manufacturing will have greater VMT due to the associated movement of materials and labor (McMullen and Eckstein, 2013).

Manufacturing accounts for 18.32% of the job market in Indiana. As can be seen in Figure 4.9, manufacturing accounts for approximately 60% of the job market for a given census tract (U.S. Census, 2013). Prior to the recession, Indiana had 513,200 jobs in the manufacturing sector. At the peak of the recession, Indiana loss 87,000 manufacturing jobs but had regained 75,200 as of 2014 (Pete, 2014). This recent rebound, paired with an aggressive tax credit and exemption program, suggests that Indiana's manufacturing jobs will continue to increase (IEDC, 2015).

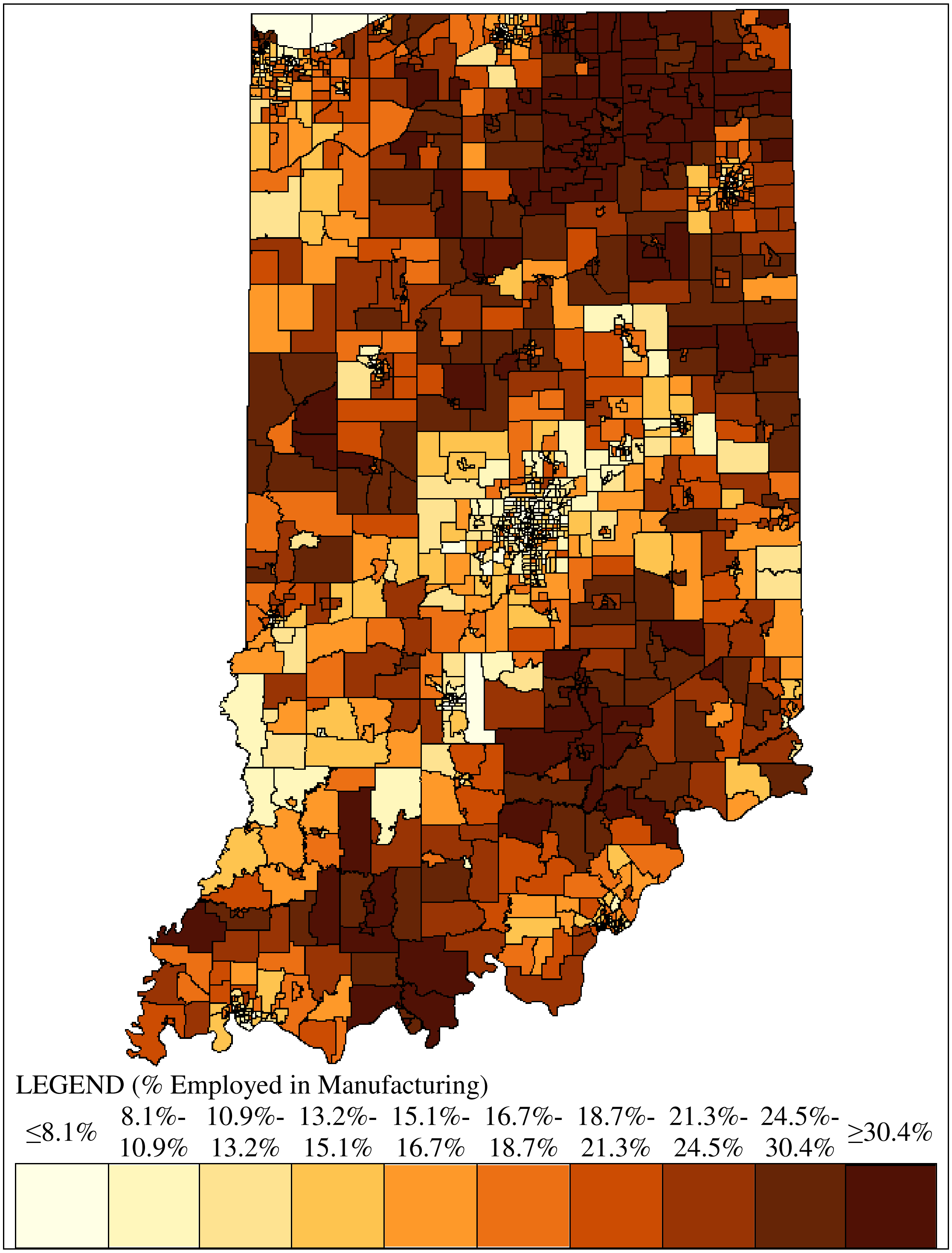


Figure 4.9 Industry (Percentage with Employed in Manufacturing) Quantile Map

4.6 Single-Occupancy Commuters

Across the United States, commuters are becoming less reliant on personal vehicles. From 2007 to 2011, 99 of the nation's 100 largest urban areas experienced a reduction in the percentage of workers commuting in private vehicles. From 2006 to 2011, the percentage of the labor force working from home increased in all 100 of the nation's largest urban areas and the percentage of households without an automobile increased in 84% of these areas (US PIRG, 2013). In Indiana, 82.4% of commutes were single-occupancy in 2012 (U.S. Census, 2013). In the urban centers of Indianapolis, Fort Wayne and Gary the percentage of single-occupancy commuters is less than the state average (Figure 4.10).

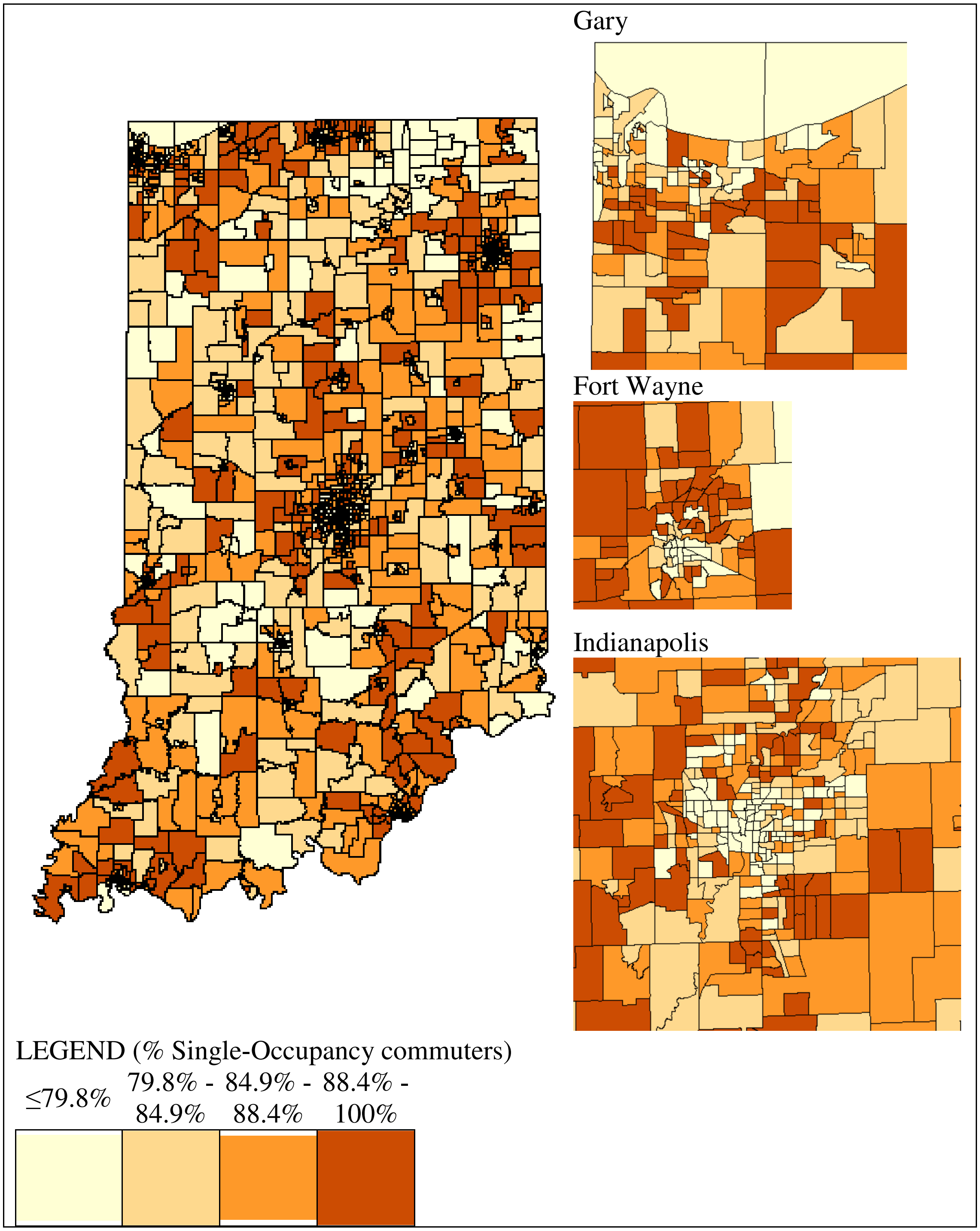


Figure 4.10 Percentage of Single-Occupancy Commuters Quantile Map

4.7 Chapter Summary

This chapter analyzed a number of social and economic factors that previous literature suggests impact vehicle use and ownership. This analysis included illustrations of how the socioeconomic data varies across the state and discussed historical trends and current legislative directives that could shift these socioeconomic characteristics in the future.

CHAPTER 5. SPATIAL ANALYSIS OF VMT AND VEHICLE USE

The amount of revenue that may be expected from transportation funding sources depends on a number of social and economic factors. For those funding sources that are related directly to the use of the transportation infrastructure, any change to the amount of travel impacts the generated funds. As such, the current research investigates the influence of underlying social and cultural factors on the extent of travel.

5.1 Introduction

The underlying causes for variance in vehicle use and ownership in geographic regions are not constant over space, which, if left unaccounted for in statistical and econometric models of vehicle use and ownership, has the potential to lead to biased, inefficient, and inconsistent results (Anselin, 1988a, 1988b, 2006; Anselin and Rey, 2014). Drivers not only drive in the census tract they live in, but they are also likely to drive in adjoining census tracts (at a rate that decreases as distance between the census tracts increases). The impact of spatial dependence can be investigated using lagged social and economic independent variables (cross-regressive terms) for local spillovers (changes in a region due to the characteristics of its local neighbors). Additionally, there may be spatial spillovers due to the fact that some drivers may avoid census tracts with greater traffic demand. The inclusion of a lagged dependent variable can account for these global spillovers (changes in a region due to the characteristics of its all other regions).

Past research projects using spatial econometric analysis to determine the relationship between socioeconomic factors and vehicle use or vehicle ownership have yielded limited results, due primarily to data limitations (Badoe and Miller, 2000). In some of the more successful research endeavors, the average individual or household VMT (for a zip code or census tract) was estimated as a function of local and lagged socioeconomic variables (Frank et. al., 2000; Cook et. al., 2012). Their results have led to increased understanding of the factors that affect an individual's VMT. However, their research could not be used to estimate the VMT for a region because individuals are not restricted to drive in the same region or state in which they live. This may be why some of these spatial models have found that cross-regressive terms (spatially lagged independent variables) and spatially lagged dependent variables are insignificant and simply reduce to a spatial error model (Cook et. al., 2012). Therefore, in order to estimate the VMT for a given region, the spatial econometric analysis must estimate the VMT of the region, not of the people who dwell in the region.

In addition to the limited past research on spatial modeling of vehicle use and ownership data, there have been spatial econometric applications in other areas of transportation research, most notably in transportation safety modeling. Spatial autocorrelation regression estimation techniques have been used to model crashes involving vehicles and pedestrians (LaScala et. al., 2000; Schneider et. al., 2000) and involving vehicles only (Aguero-Valverde and Jovanis, 2006; Li et. al., 2007; Aguero-Valverde and Jovanis, 2008; Erdogan, 2009). Furthermore, research has shown the influence of socioeconomic characteristics on vehicle crash rates across regions (Stamatiadis and Puccini, 1999; Kirk et. al., 2005).

The current research examines the socioeconomic characteristics that influence vehicle use density (average number of vehicles per centerline mile of road (VMT/Mile)) and vehicle ownership (vehicles per capita) at the census tract level. Analysis is carried out for all 1511 census tracts in the case study state; Indiana It determines that data exhibits both spatial dependence and spatial heterogeneity. Census tracts were chosen due to their relatively consistent population size (between 2,000 and 8,000) and the ability to accurately assess the relationship between vehicle use (or vehicle ownership) and socioeconomic characteristics, due to the high quality socioeconomic data available from the United States Census Bureau (U.S. Census, 2013). Chapter 4 presented a complete list of variables along with descriptive statistics. All spatial econometric modeling was completed using the spatial software GeoDa and GeodaSpace (Anselin et. al., 2006).

5.2 Methodology

Spatial process models can take a variety of forms depending on which functional components (dependent variable, independent variables, and/or error) have a spatial process applied (Anselin, 1988a, 1988b, 2006; Anselin and Rey, 2014).

In spatial statistics, terminology issues arise due to informal use of the terms spatial autocorrelation, spatial dependence, spatial variation, spatial heterogeneity, and spatial clustering. Spatial dependence occurs in geographic data when the value of a given variable at one location is dependent on other locations determined by the relative position of observations in space (Anslein, 1988b, 2006). Spatial dependence cannot be accurately measured in practice, as it is a property of the joint probability density function; however, spatial autocorrelation is a tractable moment of the joint density and therefore can be estimated. Spatial heterogeneity describes the presence of an uneven distribution of a variable over space, which can result in heteroskedasticity (Anselin, 2006).

5.2.1 Spatial Weight Matrix

The spatial weight matrix is used to define the connectivity between a location and its neighbors. Connectivity can be defined by form (rook, queen/king, k-nearest neighbors, or distance) and extent (order or number). Connectivity in first-order rook matrix are all regions that share an edge; a first-order queen/king matrix is a rook matrix that includes regions that only share a single vertex; elements in a k-nearest neighbor matrix all have the same number (k) of neighbors; and connectivity in a distance matrix is defined by the distance between the centroids of regions (Cliff and Ord, 1981; Anselin and Rey, 2014). Figure 5.1 provides a simplified diagram of six regions and defines the corresponding first-order queen weights matrix. In this example, region 1 and 2 would not be neighbors in a first-order rook matrix, but would be in a first-order queen/king matrix.

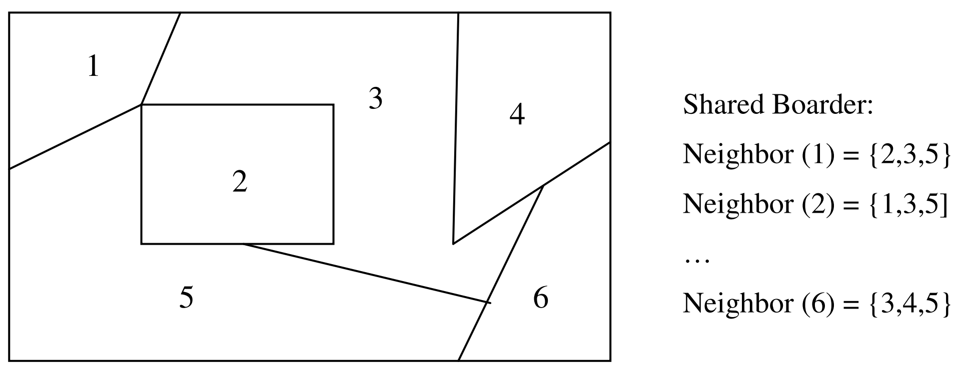


Figure 5.1 Example Neighbor Diagram

The corresponding binary and row standardized weights (binary weight divided by row sum) matrixes are presented in equations 5-1 and 5-2.

$$\widetilde{W} = \begin{pmatrix} 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 \end{pmatrix} \tag{5-1}$$

$$W = \begin{pmatrix} 0 & 1/3 & 1/3 & 0 & 1/3 & 0 \\ 1/3 & 0 & 1/3 & 0 & 1/3 & 0 \\ 1/5 & 1/5 & 0 & 1/5 & 1/5 & 1/5 \\ 0 & 0 & 1/2 & 0 & 0 & 1/2 \\ 1/4 & 1/4 & 1/4 & 0 & 0 & 1/4 \\ 0 & 0 & 1/3 & 1/3 & 1/3 & 0 \end{pmatrix} \quad \text{5-2}$$

Several weight matrix formulations were investigated, including distance and k-nearest neighbor, but ultimately a first-order queen matrix provides a more intuitive fit and a smoother connectivity distribution (frequency of the number of neighbors). Since the spatial size of the census tracts varies so greatly across the state, a k-nearest neighbors approach is believed to overestimate the spatial relationship in the larger rural tracts and underestimate the relationship of smaller urban tracts. The connectivity distribution is approximately normal with the average number of neighbors being centered on 6, as illustrated in Figure 5.2.

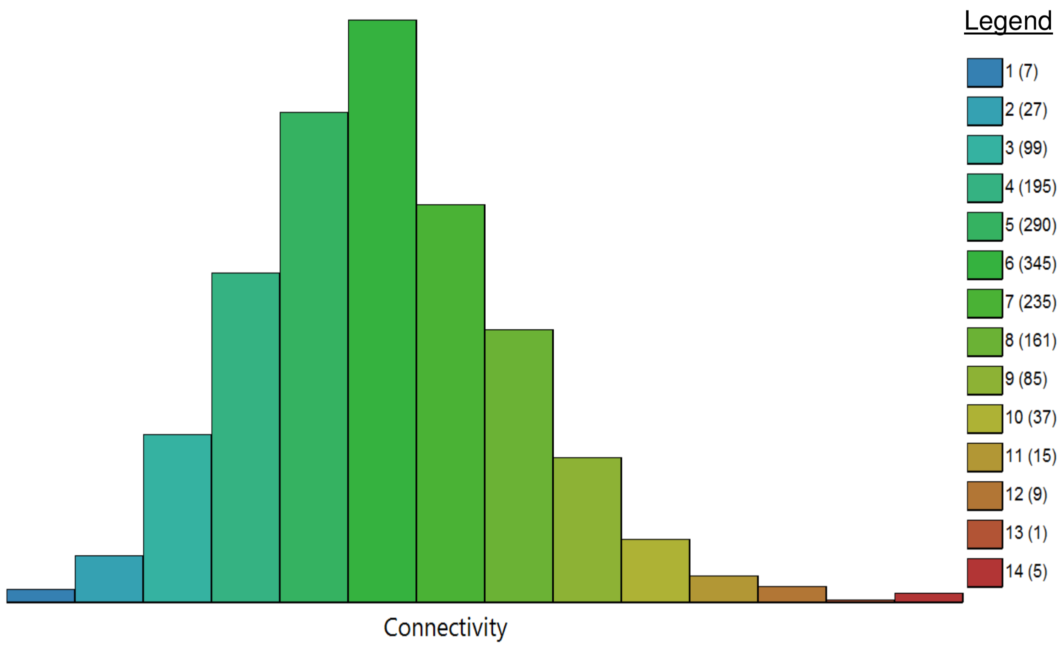


Figure 5.2 Connectivity Frequency Distribution for First-Order Queen Weights Matrix

5.2.2 Spatial Dependence

Spatial autocorrelation is a measure of the correlation a variable has with itself in space (Anselin, 1988a, 1988b, 2006; Anselin and Rey, 2014). When the value is positive, it indicates that greater values correlate with greater neighbor values (or smaller values correlate to smaller neighbor values). Negative autocorrelation occurs when greater values are correlated with smaller neighbor values (and vice versa). A preliminary analysis of spatial autocorrelation can be completed by investigating a plot of the dependent variable over space to discern if there appears to be spatial clustering of relatively higher or lower values (positive autocorrelation). This was completed separately for two variables: VMT/Mile and vehicles per capita. There are definite spatial trends in both the measure of roadway vehicle density (VMT/M) and vehicle ownership (vehicles per capita) data presented in Figure 5.3 and Figure 5.4, respectively. Vehicle travel is greater in regions with a higher percentage of NHS-functional class roads and near areas with a greater population. Conversely, the per capita vehicle ownership is reduced in these areas.

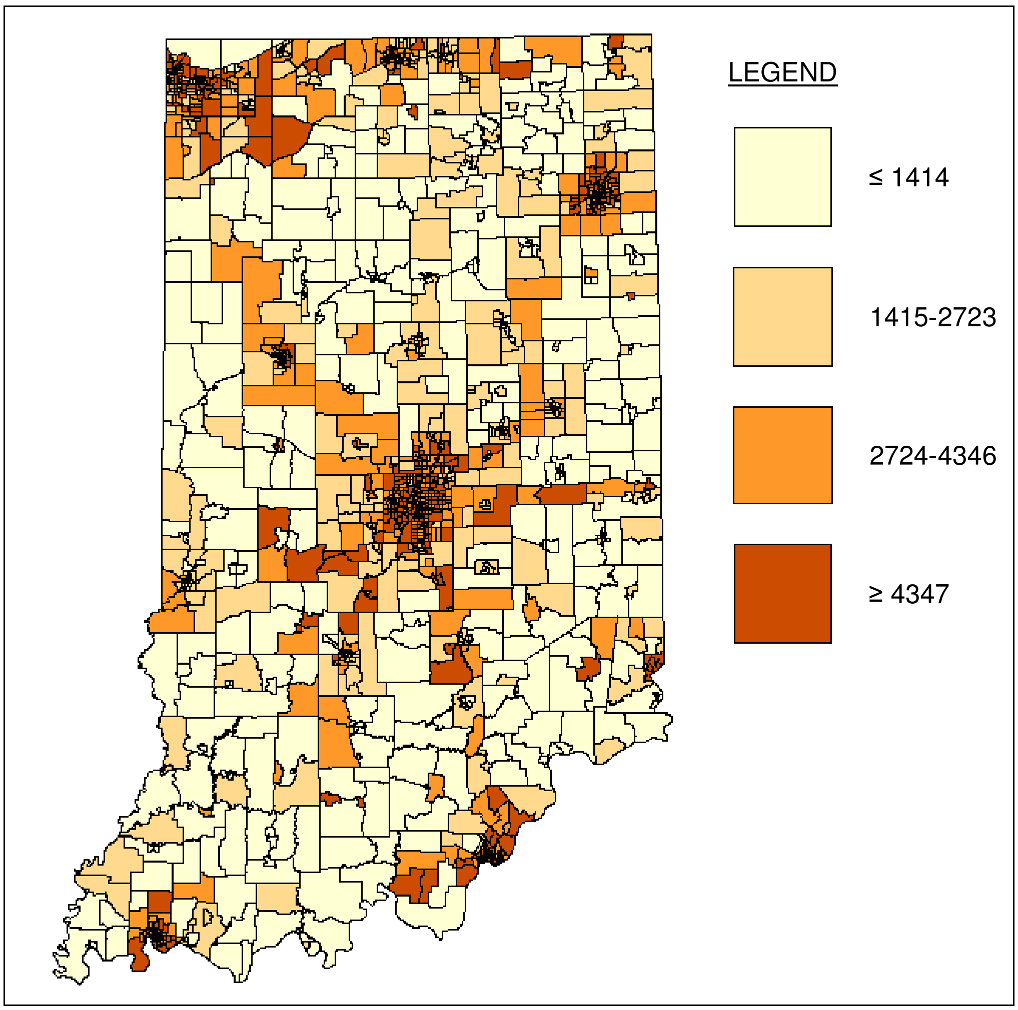


Figure 5.3 Quantile Plot for VMT/M

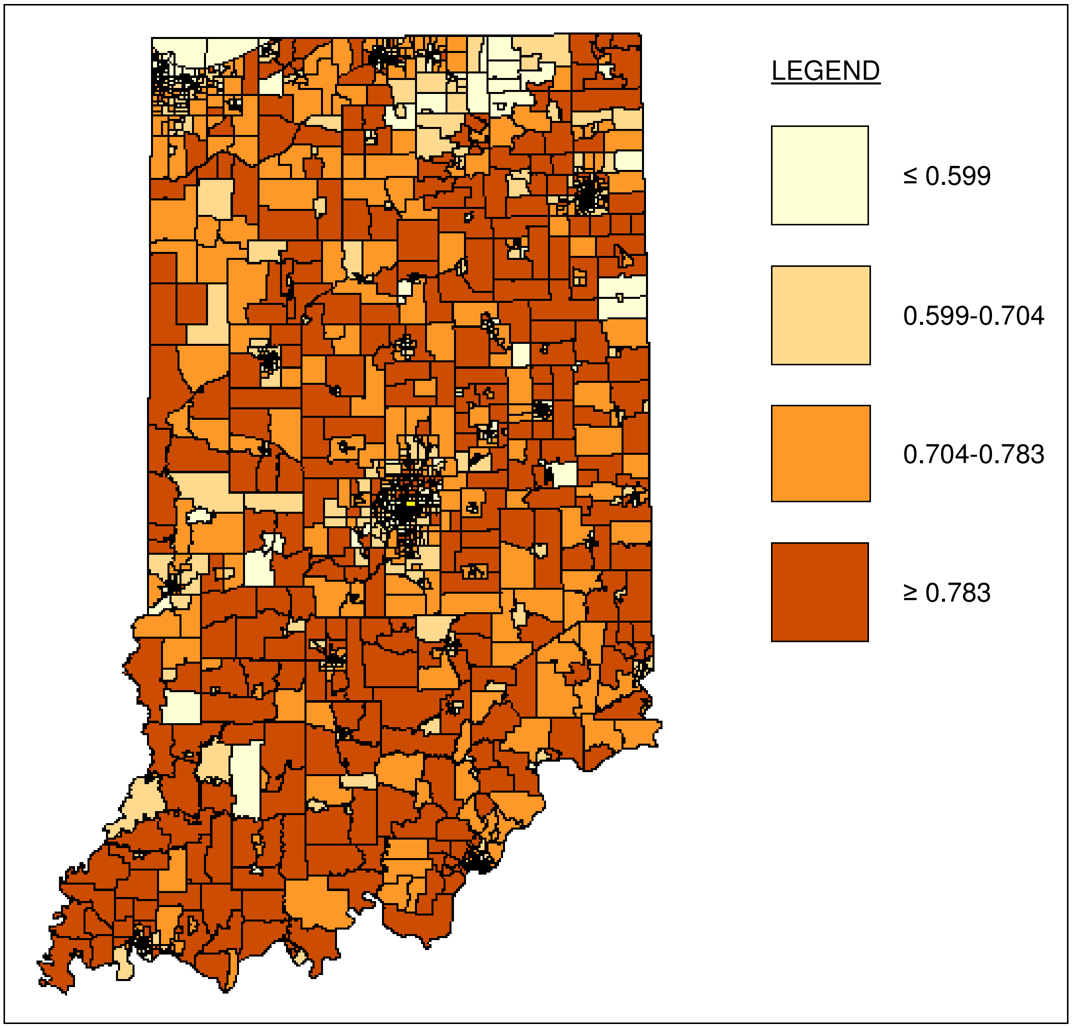


Figure 5.4 Quantile Plot for Vehicles per Capita

5.2.2.1 Measures of Spatial Autocorrelation

Moran's I is a measure of spatial autocorrelation in the dataset (Cliff and Ord, 1981). The null hypothesis is of spatial randomness, and the alternative hypothesis is of spatial dependence, with Moran's I values closer to 0 signifying the existence of spatial randomness. Moran's I is defined in Equation 5-3:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} \left(X_i - \hat{X}\right)\left(X_j - \hat{X}\right)}{\sum_i \left(X_i - \hat{X}\right)^2} \tag{5-3}$$

where $\left(X_i - \hat{X}\right)$ is the rate of region *i* centered on the mean for *i≠j*, *N* is the number of regions, and w_{ij} is the weight between region *i* and *j*.

The statistical significance of the Moran's I value cannot be calculated directly; instead, a numerical approach relying on permutations of a random variable was used. In each permutation, the regions were randomly re-assigned in space and the Moran's I statistic was calculated creating a random reference distribution (Cliff and Ord 1981). The likelihood of the actual Moran's I being drawn from the random reference distribution was then determined.

5.2.2.2 Lagrange Multiplier for Spatial Lag and Error

The Lagrange Multiplier (LM) and the robust LM for spatial lag was used to determine if the spatial error, spatial lag, or a combination would be best suited for the data (Anselin, 1988c; Anselin et. al., 1996; Anselin and Rey, 2014). The LM test for error (LM(λ)) tested the null hypothesis that spatial error coefficient (λ) is zero. This framework is presented in Equations 5-4 to 5-4.7 (Anselin, 1988c; Anselin and Rey, 2014).

$$H_0: \lambda = 0 \qquad 5\text{-}4$$

$$H_A: \lambda \neq 0 \qquad 5\text{-}4.2$$

$$\text{for } y = \beta x + \varepsilon \qquad 5\text{-}4.3$$

$$\text{where } \varepsilon = \lambda W\varepsilon + \mu \qquad 5\text{-}4.4$$

$$LM(\lambda) = \left(\left[\frac{e'We}{\sigma^2}\right]^2 / T\right) \sim \chi^2\,(1) \qquad 5\text{-}4.5$$

$$T = tr[(W' + W)] \qquad 5\text{-}4.6$$

$$s^2 = e'e/n \qquad 5\text{-}4.7$$

where $W\varepsilon$ is the spatially lagged terms for the original regression error, and μ is a vector of the remaining error terms. The Lagrange Multiplier for spatial lag tested the null hypothesis that spatial lag coefficient (ρ) is zero. This framework is presented in Equations 5-5 to 5-5.6 (Anselin, 1988c; Anselin and Rey, 2014).

$$H_0: \rho = 0 \qquad 5\text{-}5$$

$$H_A: \rho \neq 0 \qquad 5\text{-}5.2$$

$$\text{for } y = \rho Wy + X\beta + \mu \qquad 5\text{-}5.3$$

$$LM(\rho) = \left(\left[\frac{e'Wy}{\sigma^2}\right]^2 \Big/ nJ_{\rho\beta}\right) \sim \chi^2\,(1) \qquad 5\text{-}5.4$$

$$J_{\rho\beta} = [(WX\beta)'M(WX\beta) + T\sigma^2]/n\,\sigma^2 \qquad 5\text{-}5.5$$

$$M = I - X(X'X)^{-1}X' \qquad 5\text{-}5.6$$

Generalized Methods of Moments using instrumental variables was used in model estimation. Unlike the unidirectional LM tests, the robust LM test can account for both spatial lag and spatial error. In the case where more than one autocorrelation is present, such as the spatial ARAR, the robust LM test for error is robust against the presence of lag (and vice versa). The framework for the LM error robust to lag and the LM lag robust to error is presented in Equations 5-6 to 5-6.4 (Anselin et. al., 1996; Anselin, 2006).

$$\mathrm{H}_0\!: \rho = \lambda = 0 \tag{5-6}$$

$$\mathrm{H}_A\!: \rho \neq 0, \lambda \neq 0 \tag{5-6.2}$$

$$LM\lambda^* = \left[\frac{\mathrm{e'We}}{\mathrm{s}^2} - T\left(nJ_{\rho\beta}\right)^{-1}\frac{\mathrm{e'Wy}}{\mathrm{s}^2}\right]^2 \Big/ T\left[1 - T\left(nJ_{\rho\beta}\right)^{-1}\right. \tag{5-6.3}$$

$$\left[\frac{\mathrm{e'Wy}}{\mathrm{s}^2} - \frac{\mathrm{e'We}}{\mathrm{s}^2}\right]^2 /[\, nJ_{\rho\beta} - T] \tag{5-6.4}$$

5.2.3 Models for Spatial Dependence and Spatial Heterogeneity

5.2.3.1 Spatial Error Model

Spatial error models are used when spatially correlated error terms are present. If left unaccounted for in linear modeling using maximum likelihood (ML), which assumes normality or ordinary least squares (OLS), which relaxes this assumption, inefficient regression estimation could occur. The standard linear model is presented in Equation 5-7 (Anselin, 1988a)

$$y = \beta X + \mu \qquad \text{5-7}$$

Where y is an (n x 1) vector observations of the dependent variable, X is an (n x k) matrix of explanatory variables, β is a (k x 1) vector of coefficients, and μ is a (n x 1) vector of error terms. The spatial error model accounts for spatial autocorrelation by introducing the weights matrix into the error term, presented in Equation 5-8 (Anselin, 1988b, 2006; Anselin and Rey, 2014).

$$y = \mathrm{X}\beta + \varepsilon \qquad \text{5-8}$$

$$\varepsilon = \lambda \mathrm{W}\varepsilon + \mu$$

where the vector of error terms (ε) is now a function of the (n x k) weights matrix (W), the spatial autoregressive error coefficient (λ), and a vector of uncorrelated error terms (μ, with variance = σ^2). If λ is not significantly different from zero, this simplifies to the standard OLS.

5.2.3.2 Spatial Lag Model

The spatial lag and spatial cross-regressive models incorporate spatial dependence by introducing the weights matrix to lagged dependent or independent (cross-regressive) variables. Carrying out regression without spatial lag where the data is characterized by spatial lag will result in biased and inconsistent estimation. The spatial lag model takes the form shown in Equation 5-9 (Anselin 1988b, 2006; Anselin and Rey, 2014).

$$y = \rho Wy + X\beta + \mu \tag{5-9}$$

where *Wy* is the spatial lag term, and ρ is a vector of the spatial coefficient for the lagged dependent variable. Like the spatial error model, the spatial lag model accounts for global spillovers regardless of the size of the weights matrix. The lagged dependent variable is an endogenous explanatory variable that violates the assumption of OLS estimation, which would result in biased results. This issue can be overcome with two-stage least squares estimation (2SLS), a special case of instrumental variables (IV). IV estimation relies on a set of instruments that are correlated with the lagged dependent variable, but are not correlated with the error term or multi-collinear (Anselin and Rey, 2014). The instruments are then used as a proxy for the endogenous explanatory variable.

The Anselin-Kelejian (AK) test can then be used to determine if there is spatial autocorrelation remaining in the residuals of the 2SLS estimation. The Anselin-Kelejian test is the Moran's I statistic (discussed in Section 5.2.2.1) applied to the residuals of the 2SLS estimation (Anselin and Kelejian, 1997).

5.2.3.3 Spatial Cross-Regressive Model

The cross-regressive model can be thought of as a local spatial model because spatial spillovers are limited to the extent of the weights matrix. The spatial cross-regressive model takes the form shown in Equation 5-10 (Anselin, 2006; Anselin and Rey, 2014).

$$y = X\beta + \gamma WZ + \mu \tag{5-10}$$

where Z is a vector of linearly independent Xs, and γ is the spatial coefficient for the lagged explanatory variables.

5.2.3.4 Spatial Lag and Error Model

The spatial ARAR model (autoregressive-autoregressive) is a combination of the spatial error model and the spatial lag model, and is defined in Equation 5-11 (Anselin, 2006, Anselin and Rey, 2014).

$$y = \rho Wy + X\beta + \lambda W\varepsilon + \mu \tag{5-11}$$

5.2.3.5 Spatial Durbin Model (Spatial Lag and Cross-Regressive)

The spatial Durbin model is a combination of the spatial lag and spatial cross-regressive models, and is defined in Equation 5-12 (Anselin, 2006, Anselin and Rey, 2014).

$$y = \rho Wy + \beta x + \gamma WZ + \mu \tag{5-12}$$

5.2.3.6 The General Spatial Durbin

A general spatial Durbin model incorporates spatial lag, spatial error, and cross regression. The model form is provided in Equation 5-13 (Anselin, 2006; Anselin and Rey, 2014). When this is simplified (Equation 5-14), a double spatial process on the error terms becomes evident. The marginal effects (Equation 5-15) become complex, as a change in X changes X and WX. The direct effects vary by spatial unit due to higher order feedback effects, whereas the indirect marginal effects incorporate spillover effects. The diagonal components of the marginal effects matrix (∂y/∂x) are the direct effects; the off-diagonal are the indirect effects. The average total effect is defined as $(1/1-\rho)\beta_k$.

$$y = \rho \mathrm{Wy} + \mathrm{X}\beta + \delta \mathrm{WX} + (\mathrm{I} - \rho \mathrm{W})^{-1}\mu \tag{5-13}$$

$$y = (\mathrm{I} - \rho \mathrm{W})^{-1}[\beta x + \delta \mathrm{WX} + (\mathrm{I} - \rho \mathrm{W})^{-1}\mu] \tag{5-14}$$

$$\frac{\partial y}{\partial x} = (\mathrm{I} - \rho \mathrm{W})^{-1}(\beta_k + \delta \mathrm{W}) \tag{5-15}$$

5.3 Vehicle Use (VMT/M) Model Results

5.3.1 Introduction

Traffic volume is a driving factor in both the amount of funding needed and the amount of revenue available for transportation infrastructure. In terms of needed funding, it is well established that transportation infrastructure deterioration is a function of loading. In addition, the amount of revenue that can be generated by any user-based taxation or fee structure is primarily dependent on the amount of travel. Travel and infrastructure loading can be characterized by the number, type, and weight of the vehicles that travel a given segment of road. Averaging these characteristics over a geographic region that includes hundreds of road segments can provide an assessment of the relative level of traffic within the region. The travel volume characteristic of greatest concern in the current research is the road usage at the census track level in terms of VMT. Due to the fact that the number of centerline miles (CLM) varies greatly between census tracks, comparing only census-track VMT would skew the results in favor of larger geographic regions. Therefore, daily VMT was weighted by the number of CLM, providing a value for the daily Vehicle Miles Traveled per Mile (VMT/M) for each tract, and thereby facilitating a more accurate comparison. These values are presented in Figure 5.5.

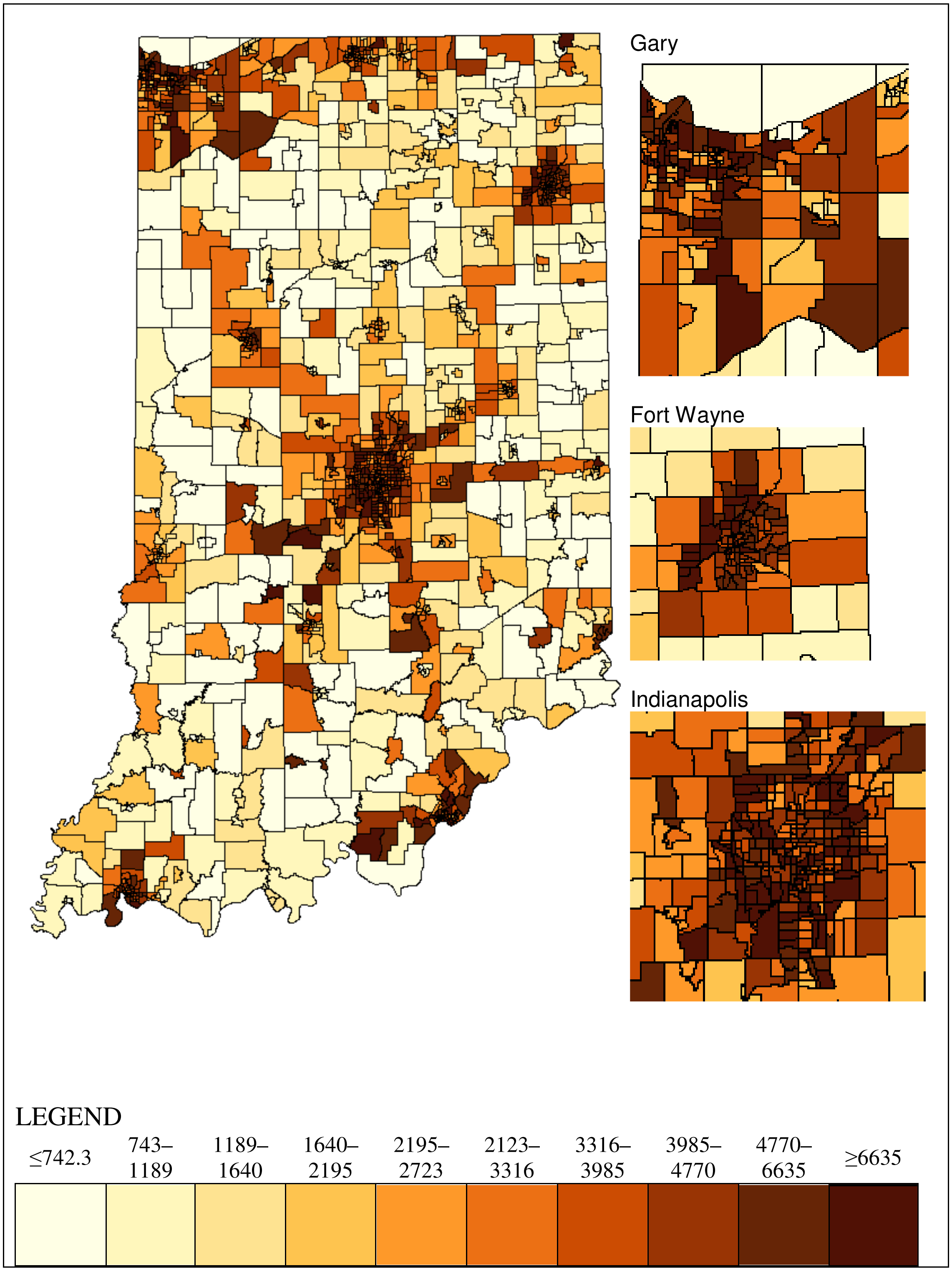


Figure 5.5 Traffic Loading (VMT/M) Map

5.3.2 Moran's I

A scatter plot of the Moran's I for the dependent variable (VMT/M) is computed by converting the raw values to a stand score and then plotting the value of y versus the lagged value of y (the lagged value of y is the product of y and the weights matrix) (Cliff and Ord, 1981). The slope of the best fit line shown in the Moran's I scatter plot in Figure 5.6 is the value of Moran's I. The Moran's I was calculated to be 0.4408 with a corresponding z-score and p-value of 28.64 and 0.001, respectively, and was determined using 999 random permutations. This means that the null hypothesis of no spatial autocorrelation can be rejected at a 99.9% level of confidence. Inferences based on OLS estimation without accounting for spatial autocorrelation are biased and inconsistent (Anselin, 1988a, 1988b, 2006; Anselin and Rey, 2014).

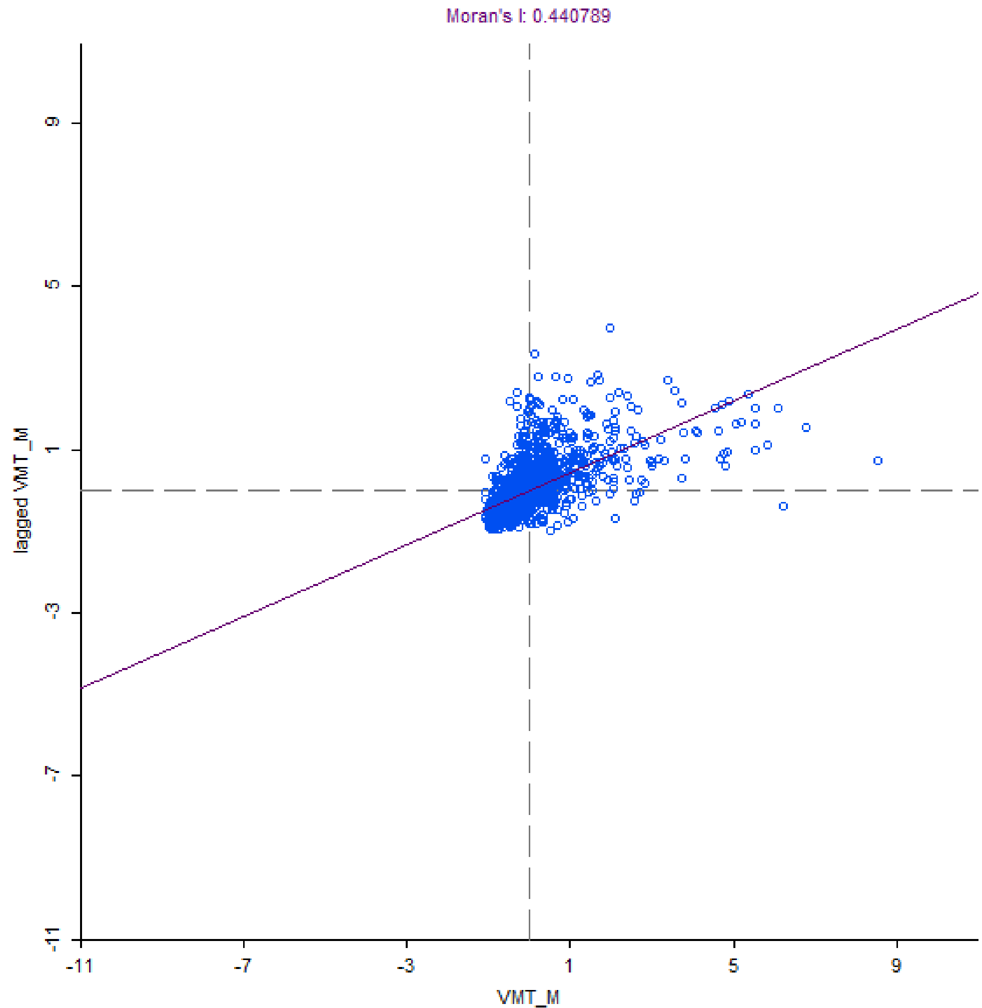


Figure 5.6 Moran's I Scatter Plot for VMT/M

The local indicator of spatial association (LISA) cluster map (Figure 5.7) shows regions of spatial clustering. "The LISA for each observation [say, a small region among a set of regions] gives an indication of significant spatial clustering of similar values around that observation. The sum of LISAs for all observations is proportional to a global indicator of spatial association" (Anselin, 1995). Positive autocorrelation is evident in 534 census tracts, compared to only 47 census tracts that experience negative autocorrelation. High-high spatial clustering (high values correlate with high neighboring values) were evident in the small urban census tracts in Indianapolis, Fort Wayne, Evansville, and Louisville, whereas a significant number of rural census tracts experience low-low spatial clustering (high values correlate with high neighboring values).

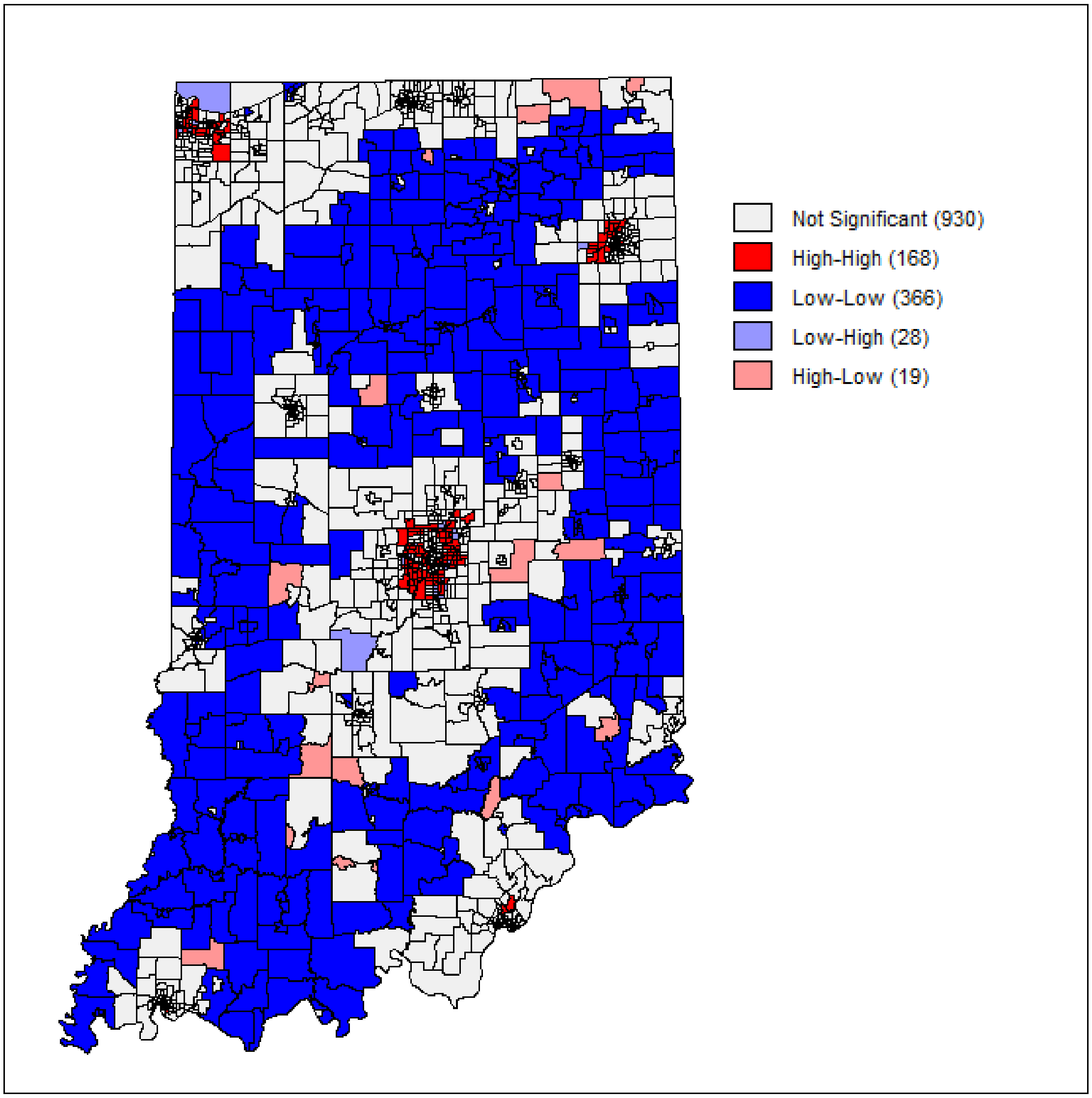


Figure 5-7 LISA Cluster Map for VMT/M

5.3.3 Aspatial (Non-Spatial) Model Results

Prior to developing a model for spatial estimation, an aspatial (non-spatial) model for traffic demand (census tract VMT/M) was developed. It was determined that the census tract VMT/M is a function of seven socioeconomic variables, including the median household income in 2012 dollars, the percentage of population with health insurance, the percentage of the population who live below the poverty line, the percentage of the labor force employed in manufacturing, the percentage of the population who have obtained at least a high school diploma, the percentage of population who commute to work as a single driver (compared to those who carpool, use public transit, walk, bicycle, or telecommute/work from home), and population. The census tract VMT/M was also dependent on the size of the census tract (in square miles), the percentage of auto VMT in the total census tract VMT, the percentage of class 9 truck (two unit, five axle) VMT in the total census tract truck VMT, the percentage of all centerline miles (CLM) that are on state-owned routes, and household density (households per square mile). The results of this model are presented in Table 5.1.

Table 5.1 Aspatial Model Results

Response Variable: Census Tract VMT/M		
Variable	**Coefficient**	**t-stat**
Constant	5119.41	5.590
Median Household Income (2012 dollars)	0.0231	4.123
% Health Ins. (0–100%)	-17.25	-1.389
% In Poverty (0–100%)	30.48	3.917
% Labor Force Manufacturing (0–100%)	-90.72	-11.021
% High School Grad. (0–100%)	-21.94	-1.874
Household Density (HH/sq. mi.)	1.19	10.381
Land Area (sq. mi.)	-28.74	-13.326
% Centerline Miles on State Network	6948.38	16.090
Population	0.0853	2.392
% Auto (0.0–1.0)	-4850.51	-4.741
% Single Occ. Commuters (0.0–1.0)	3962.58	5.184
% of Trucks that are Class 9 (0.0–1.0)	3471.28	11.261
Model Statistics		
R-squared	0.4251	
Adjusted R-squared	0.4205	
Number of Observations	1511	
Number of Variables	13	

The adjusted R-squared value indicates that the model is explaining 42% of the variance exhibited in the census tract VMT/M data. These results should be considered strong considering the complexities in regional travel data.

5.3.3.1 Specification Testing

The aspatial model has a corresponding multicollinearity condition number of 51.82. This value is used as an indication of the degree to which explanatory variables show a linear relationship. In statistics, it is generally agreed upon that multicollinearity should be addressed if the condition number is greater than 30 or 50 (Anselin and Rey, 2014). However, the multicollinearity condition number is susceptible to the presence of indicator variables in the model.

Typically, the specification robust test (White test) is used to test for heteroskedasticity. However, the White test is unable to be estimated when the multicollinearity condition number is greater than 30. For the aspatial VMT/M model, the multicollinearity number was 51.82, indicating the presence of heteroskedasticity. Therefore, White-adjusted standard errors are used.

The Jarque-Bera test for non-normality of the error terms was significant at a 99% level of confidence (Jarque and Bera, 1980). Therefore, in order to test the residuals for homoscedasticity (consistency of the error variance), a Koenker–Basset test, a variant of the Breusch-Pagan test (Breusch and Pagen, 1979), was used because, unlike the Breusch-Pagan test, it does not assume normality of the error terms. The Koenker-Basset test value was significant at a 99% level of confidence. To account for heterogeneity, White-adjusted standard errors that are robust to heteroskedasticity were used (White, 1980).

5.3.4 Model for Spatial Dependence

The Moran's I (discussed in Section 5.2.2.1) was determined to be 0.441 with a corresponding z-score and p-value of 28.64 and 0.001, respectively, which indicates statically significant evidence of spatial heterogeneity. This was partially addressed through the development of spatial regimes for urban and rural census tracts. Spatial regimes allow the model to estimate different intercepts and slopes for observations (census tracts) in rural and urban areas. The results of the urban/rural spatial regime OLS estimation with White-adjusted errors are presented in Table 5.2. A 90% level of significance is used throughout, unless otherwise noted. Since the spatial lag and spatial error have not been introduced into the modeling framework, the estimated coefficients are the marginal effects.

Table 5.2 Standard OLS Model Results with White-Adjusted Standard Errors and Spatial Regimes

Response Variable: Census Tract VMT/M				
	Rural Regime		**Urban Regime**	
Variable	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	2048.09	1.732	14352.57	2.037
Median HH Inc. (2012 dollars)	0.0315	3.905	0.0229	4.054
% Health Ins. (0–100%)	-11.47	-0.616	-34.61	-1.571
% In Poverty (0–100%)	-17.59	-0.512	16.94	1.334
% L. Force Man. (0–100%)	-29.51	-2.361	-109.48	-9.522
% High School (0–100%)	5.05	0.197	-27.21	-1.766
HH Density (HH/sq. mi.)	1.83	0.396	0.8239	5.158
Land Area (sq. mi.)	-11.16	-4.716	-73.88	-7.691
% CLM on State	5091.94	5.553	10602.91	6.091
Population	0.0862	1.378	0.0946	2.595
% Auto (0.0–1.0)	-2499.76	-1.275	-11475.76	-2.468
% Single Occ. Commuters (0.0–1.0)	-513.6	-0.499	4038.96	3.271
% of Trucks that are Class 9 (0.0–1.0)	2209.22	1.535	2522.71	5.483
Model Statistics				
R-squared	0.4750		0.4260	
Adjusted R-squared	0.4588		0.4198	
Number of Observations	400		1111	
Number of Variables	13		13	

The median household income was positive and statistically significant in both the rural and urban regimes. The percentage of the labor force employed in manufacturing was negative and statistically significant in both regimes. This may indicate that those who work in this industry typically have shorter commutes. The percentage of adults with at least a high school diploma is negative and significant in the urban regime, but it was positive and insignificant in the rural regime. This reflects the propensity for those with more education to be able to afford to live closer to urban centers for work and leisure, therefore to drive less. The household density and population were positive in both regimes but were only significant in the urban regime. A greater household density may indicate a more residential area, which would mean individuals would have to drive further for services. Land area was negative and significant in both regimes, which may reflect variation in the extent of urbanization within each regime. The percentage of the road centerline miles (CLM) on the state-owned network was positive and significant in both regimes, which is to be expected because state-owned routes are built in response to travel demand. The percentage of automobiles in the traffic stream was negative and significant, and the percentage of class 9 trucks (two unit, 5 axle) was positive and significant in the urban regime. Lastly, the percentage of single-occupancy commuters was positive and significant in the urban regime, which is expected because carpooling, public transit, and walking would all reduce the number of vehicles on the road.

Table 5.3 Chow Test for Spatial Regimes (VMT/M Model)

Variable	**DF**	**Value**	**Probability**
Constant	1	2.965	0.085
Median HH Inc. (2012 dollars)	1	0.752	0.386
% Health Ins. (0–100%)	1	0.643	0.423
% In Poverty (0–100%)	1	0.890	0.346
% Labor Force Manufacturing (0–100%)	1	22.167	0.000
% High School Graduate (0–100%)	1	1.163	0.281
Household Density (HH/sq. mi.)	1	0.047	0.828
Land Area (sq. mi.)	1	40.199	0.000
% CLM on State	1	7.846	0.005
Population	1	0.014	0.907
% Auto (0.0–1.0)	1	3.165	0.075
% Single Occ. Commuters (0.0–1.0)	1	8.020	0.005
% of Trucks that are Class 9 (0.0–1.0)	1	0.043	0.836
Global test	13	166.023	0.000

The spatial Chow test (Anselin, 1988a) is a variant of the standard Chow test and is used to determine if the difference in the coefficients for the spatial regimes is statistically significant. The spatial Chow test for each explanatory variable (provided in Table 5.3) indicates that the percentage of the labor force in manufacturing, land area, percentage of the CLM on the state network, and percentage of single-occupancy commuters are significant at a 95% level of confidence, and the percentage of automobiles in the traffic stream is significant at a 90% level of confidence. The remaining variables would not need to be estimated separately for each regime. The global Chow test is significant at 99% level of confidence, supporting the use of the spatial regimes (Chow, 1960).

5.3.5 Cross-Regressive Terms

It is believed that, since an individual's travel is not limited to within one's own census tract, socioeconomic characteristics of both the census tract and its neighbors will be significant in the estimation of VMT/M. Therefore, a cross-regressive OLS model with White-adjusted standard errors and spatial regimes was estimated for the VMT/M census tract data. The cross-regressive independent variables found to be significant in one or more of the regimes were the total number of households, average household size, household density, median household income, mean household income, percentage unemployed, percentage with at least a high school diploma, percentage with at least a bachelor's degree, and percentage of single-occupancy commuters. The intuitiveness of these variables is discussed in Section 5.3.7 that follows.

Table 5.4 Cross-Regressive Model Results with White-Adjusted Standard Errors and Spatial Regimes

Response Variable: Census Tract VMT/M				
	Rural Regime		**Urban Regime**	
Variable	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	-1918.18	-1.055	10238.96	1.641
Median HH Inc. (2012 dollars)	0.0261	3.035	0.0014	0.187
% Health Ins. (0–100%)	-19.93	-1.057	-23.23	-1.196
% In Poverty (0–100%)	4.9	0.191	6.21	0.614
% Labor Force Manuf. (0–100%)	-20.22	-2.819	-62.4	-5.615
% High School Grad. (0–100%)	-4.9	-0.208	-0.1813	-0.011
Household Density (HH/sq. mi.)	3.94	1.051	0.0041	0.027
Land Area (sq. mi.)	-7.39	-3.651	-54.48	-6.657
% CLM on State	4989.04	5.398	11680.96	7.178
Population	-0.0231	-0.332	0.0986	2.601
% Auto (0.0–1.0)	-4115.36	-3.301	-11254.7	-3.057
% Single Occ. Commuters (0.0–1.0)	1151.2	1.004	2667.82	2.587
% of Trucks that are Class 9 (0.0–1.0)	1717.72	1.854	2860.46	6.750
Cross-Regressive Terms				
Total HH	1.22	3.658	0.2885	1.509
Average HH Size (inhabitants)	367.27	0.757	-1127.34	-2.309
Median HH Inc. (2012 dollars)	0.023	0.767	0.0666	2.205
Mean HH Inc. (2012 dollars)	-0.0126	-0.509	-0.0383	-1.593
% Unemployed (0–100%)	36.6	0.629	76.26	3.130
% High School Grad. (0–100%)	22.53	0.623	-103.63	-4.674
% Bachelor's Degree (0–100%)	-12.16	-0.250	52.65	3.203
Household Density (HH/sq. mi.)	2.97	2.075	2.22	9.328
% Single Occ. Commuters (0.0–1.0)	84.56	0.031	10825.33	5.624
Model Statistics				
R-squared	0.5388		0.5102	
Adjusted R-squared	0.5132		0.5008	
Number of Observations	400		1111	
Number of Variables	22		22	

5.3.6 Lagrange Multiplier Results for VMT/M Models

The functional forms for the Lagrange Multiple (LM) and robust LM were presented in section 5.2.2.2 in equations 5-4 to 5-7. The results for LM and robust LM test are presented in Table 5.5. The LM tests for spatial lag and spatial error are both significant at a 99.9% level of confidence. Therefore, the robust LM for spatial lag and error is then computed to determine if true underlying process only contains one of the two spatial components. This is required because the LM test for spatial lag is affected by the presence of spatial error (and vice versa). The results of the robust LM test for lag and the robust LM for error are significant at a 99.5% and 99.9% level of confidence. This indicates that the spatial Durbin model may be slightly better suited to the data compared to the auto-regressive auto-regressive model (ARAR); however, the SARMA LM, which accounts for both spatial lag and spatial error, indicates that both spatial lag and spatial error may be present.

Table 5.5 Lagrange Multiplier Test Results for Spatial Lag and Spatial Error (VMT/M Model)

Test	**DF**	**Value**	**Probability**
Lagrange Multiplier (lag)	1	179.175	0.000
Robust LM (lag)	1	32.181	0.000
Lagrange Multiplier (error)	1	154.715	0.000
Robust LM (error)	1	7.721	0.006
Lagrange Multiplier (SARMA)	2	186.896	0.000

To check for remaining spatial autocorrelation in the residuals, the spatial lag model was run without spatial error to produce an Anselin-Kelejian Test for spatial dependence (Anselin & Kelejian, 1997). The test value was 0.544 with 1 degree of freedom for the spatial lag model without spatial regimes, which is statistically insignificant. Therefore, the spatial Durbin model, which incorporates spatial lag but not spatial error, is best suited for the data.

5.3.7 Final Model Specifications (Spatial Durbin)

The VMT/M dataset was determined to exhibit spatial dependence (lag and cross-regressive) but did not exhibit spatial error once separate regimes were defined for rural and urban census tracts. Therefore, a spatial Durbin was determined to be best suited to the data. The final model specification (presented in Table 5.6) includes a constant term, eight independent variables, eight cross-regressive terms, and a spatial lag of the VMT/M variable. Coefficient estimates were found to be statistically significant at a 95% level of confidence unless otherwise noted.

Six of the variables were statically significant in at least one regime but insignificant as cross-regressive terms. Median household income was positive and significant in the rural regime, but was insignificant in the urban regime and insignificant as a cross-regressive term. This means that rural tracts that have a greater household income are expected to have a greater VMT/M. This could be due to the propensity of higher earners in rural tracts to seek larger properties that are located further from stores and industries, requiring more driving. The coefficient for the percentage of the labor force employed in manufacturing was significant and negative in both regimes. This indicates that those employed in this industry might have shorter commutes. The coefficient for the size of the census tract (land area) was negative and significant in both regimes, reflecting the relative urbanization (all else being equal), as larger census tracts can be considered more rural regardless of their classification. An increase in population would increase the VMT/M in urban census tracts reflecting an increase in local travel. The percentage of the road centerline miles (CLM) on the state-owned network was positive and significant in both regimes, which are to be expected because state-owned routes are built in response to travel demand. The coefficient for the percentage of class 9 trucks (two unit 5 axle) in the truck traffic stream on the state network is positive in the urban regime. This may reflect a discrepancy in pavement condition, as long-haul truck drivers prefer to drive on pavements with increased ride quality. As drivers of other vehicle classes follow suit, the overall VMT per mile increases. Lastly, the percentage of automobiles in the traffic stream reduced the overall VMT/M in the census tract for both urban and rural areas.

The percentage of the population with at least a bachelor’s degree and the percentage of single-occupancy commuters were a significant variable and cross-regressive term in at least one regime. The percentage of the population with at least a bachelor’s degree had a positive coefficient as a direct variable and a negative coefficient as a cross-regressive term. This indicates that, for census tracts with more jobs requiring a bachelor's degree, more of their employees live within the census tract, and therefore, there is a lower VMT/M. But also, due to the attraction of employees from neighboring census tracts, VMT/M is likely to increase. An increase in the percentage of single-occupancy commuters within an urban census tract or within its neighboring census tracts will increase the VMT/M (it is only statistically significant at a 90% level of confidence as a direct variable). This is logical, as the alternatives would be to carpool, take mass transit, walk, or telecommute, which would all reduce the traffic volume (VMT/M). It is believed that this variable is statically insignificant in the rural regimes because the number of commuting alternatives is severely limited.

Six other census tract characteristics were significant as cross-regressive terms only. An increase in number of households in neighboring census tracts would increase the expected VMT/M for rural census tracts, simply reflecting the additional travel demand. The household size of neighboring tracts was significant at a 90% level of confidence in the urban regime. This could reflect the propensity for large families to have less free time and thus shop locally to a greater extent in order to save time. An increase in household density of neighboring census tracts is expected to increase the VMT/M in both urban and rural areas. This is logical because areas with a high population density are more residential, and therefore, inhabitants are more likely to be forced outside of the census tracts for work and shopping. An increase in the unemployment rate in neighboring areas will increase the travel in urban census tracts. This may mean that the unemployed are traveling in search of work, or it may mean that this group simply has more time to travel in general. An increase in the percentage of the population without health insurance in neighboring tracts decreases the travel in urban census tracts. This may indicate that this group does not have the financial means to travel.

Lastly, the coefficient for the spatially lagged dependent variable (VMT/M) was positive and significant in the urban regime. This reflects the desire for drivers to avoid areas with higher traffic volumes. Therefore, if the traffic volume in neighboring tracts increases, one would be more likely to avoid those tracts and shift to driving in the tract in question. The lagged dependent variable was insignificant in the rural regime due to the relatively larger size of rural census tracts. The larger size does not allow drivers to easily avoid areas with higher traffic volumes. The model showed good statistical fit with spatial pseudo R-squared values of 0.5317 and 0.5112 for the rural and urban census tract regimes, respectively.

Table 5.6 Spatial Durbin Model Results with Cross-Regressive Terms, White-Adjusted Standard Errors, and Spatial Regimes

Response Variable: Census Tract VMT/M				
	Rural Regime		**Urban Regime**	
Variable	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	-1550.28	-1.021	6527.57	1.286
Median HH Inc. (2012 dollars)	0.0206	2.767	0.0016	0.261
% Labor Force Manufacturing (0–100%)	-18.39	-2.718	-33.57	-3.378
% Bachelor's Degree (0–100%)	7.67	0.331	-20.35	-2.553
Land Area (sq. mi.)	-9.37	-6.315	-51.81	-7.129
Population	-0.014	-0.185	0.0905	2.641
% CLM on State	5013.47	5.679	11246.32	7.617
% Single Occ. Commuters (0–1.0)	-327.38	-0.152	1585.71	1.704
% Trucks that are Class 9 (State Network) (0–1.0)	1538.97	1.919	2030.24	5.029
% Auto (0–1.0)	-4421.18	-4.186	-11026.2	-2.830
Cross-Regressive Terms				
Total HH	1.22	3.513	0.1855	1.184
Average HH Size (inhabitants)	549.21	1.166	-599.34	-1.647
Household Density (HH/sq. mi.)	2.67	2.095	1.46	7.311
% Unemployed (0–100%)	15.88	0.260	60.86	2.760
% Bachelor's Degree (0–100%)	-6.85	-0.254	47.49	3.708
% Health Ins. (0–100%)	-16.92	-0.711	-48.17	-1.845
% Single Occ. Commuters (0.0–1.0)	3512.19	0.916	7451.87	4.422
Lagged Dependent Variable				
VMT/M	0.028	0.360	0.3879	7.059
Model Statistics				
Pseudo R-squared	0.5317		0.5945	
Spatial Pseudo R-squared	0.5317		0.5112	
Number of Observations	400		1111	
Number of Variables	18		18	

5.3.8 Vehicle Use Summary

The extent of travel is the main component in any mileage-based revenue structure, and it also is the driving factor of transportation infrastructure deterioration and thus funding needs for repairs.

The relative level of traffic within the region can be assessed by averaging the daily traffic over all road segments in that region. The census tract-level VMT was weighted by the number of CLM providing an assessment of the daily travel in each census tract (VMT/M). The analysis presented in Section 5.3 quantified the extent to which the socioeconomic characteristics of a census tract impact the expected VMT/M.

Aspatial and spatial modeling techniques were implemented to determine the model that would best account for the underlying spatial dependence and heterogeneity. White-adjusted standard errors were used to correct for heteroskedasticity in the VMT/M data. Spatial regimes were developed for urban and rural census tracts and were found to be statistically significant using the global Chow test statistic. The cross-regressive terms that were found to be significant in the spatial regime model were the total number of households, average household size, household density, median household income, average household income, percentage unemployed, percentage with at least a high school diploma, percentage with at least a bachelor's degree, and percentage of single-occupancy commuters. Then the Lagrange Multiplier test for lag, robust lag, error, and robust error led to the final model specification of a spatial Durbin model. The lagged dependent variable was found to be significant at a 95% level of confidence in urban regime but insignificant in the rural regime.

Table 5.7 provides a comparison of the model statistics for each stage of model development. The results show that goodness-of-fit (adjust R-squared) improved from 0.421 in the base OLS model to 0.459 and 0.420 in the rural and urban regimes. When cross-regressive terms were introduced, the rural and urban adjusted r-squared values improved to 0.513 and 0.501, respectively. Lastly, when spatial lag of the dependent variable, VMT/M, was included in the model, the goodness-of-fit improved to 0.532 and 0.511 for the rural and urban regimes, respectively. To perform model validation, the estimated VMT/M for each census tract was multiplied by the number of centerline miles in each tract and summed for all tracts in the state to provide an estimate for the state VMT. The results show that the model slightly under-predicted the state VMT (estimated in Chapter 3) by 10.1%. This is a improvement over the aspatial model (Table 5.1) which under-predicted the state VMT by 44.1%

Table 5.7 Comparison of Model Statistics

Model	**R^2 / Pseudo R^2**	**Adj. R^2 / Spatial Pseudo R^2**	**# of Obs.**	**# of Var.**
OLS	0.4251	0.4205	1511	13
Rural Regime				
OLS with Spatial Regimes and White-Adjusted Standard Errors	0.4750	0.4588	400	13
Cross-Regressive OLS Model Results with White-Adjusted Standard Errors and Spatial Regimes	0.5388	0.5132	400	22
Spatial Durbin Model Results with Cross-Regressive Terms, White-Adjusted Standard Errors, and Spatial Regimes	0.5317	0.5317	400	18
Urban Regime				
OLS with Spatial Regimes and White-Adjusted Standard Errors	0.4260	0.4198	1111	13
Cross-Regressive OLS Model Results with White-Adjusted Standard Errors and Spatial Regimes	0.5102	0.5008	1111	22
Spatial Durbin Model Results with Cross-Regressive Terms, White-Adjusted Standard Errors, and Spatial Regimes	0.5945	0.5112	1111	18

5.4 Vehicles per Capita Model Results

5.4.1 Introduction

A portion of the costs incurred by transportation agencies cannot be directly attributed to the use of the transportation facility. These costs, such as administrative overhead, planning, and environmental impact analysis, are incurred by the agency regardless of whether a given driver uses a facility once a day or once in a lifetime. Additionally, as material technologies increase, a greater fraction of the costs of infrastructure construction and maintenance will become common to all users—that is, the costs will increasingly become a function of vehicle ownership instead of use. These and other factors are part of the motivation behind collecting fees, such as vehicle registration, that consider annual infrastructure use as a binary variable (either a driver uses the infrastructure or does not) instead of reflecting the extent of vehicle use in terms of vehicle-miles traveled or vehicle weight-miles traveled. It is then logical to recognize that the number of vehicles available from which to collect these fees would be a significant factor in an agency's ability to generate the funds necessary for the ongoing operation of its infrastructure. The total number of vehicles per capita was analyzed at the census tract level so that the influence of social and economic factors could be quantified. A quantile map of the vehicles per capita is provided in Figure 5-8.

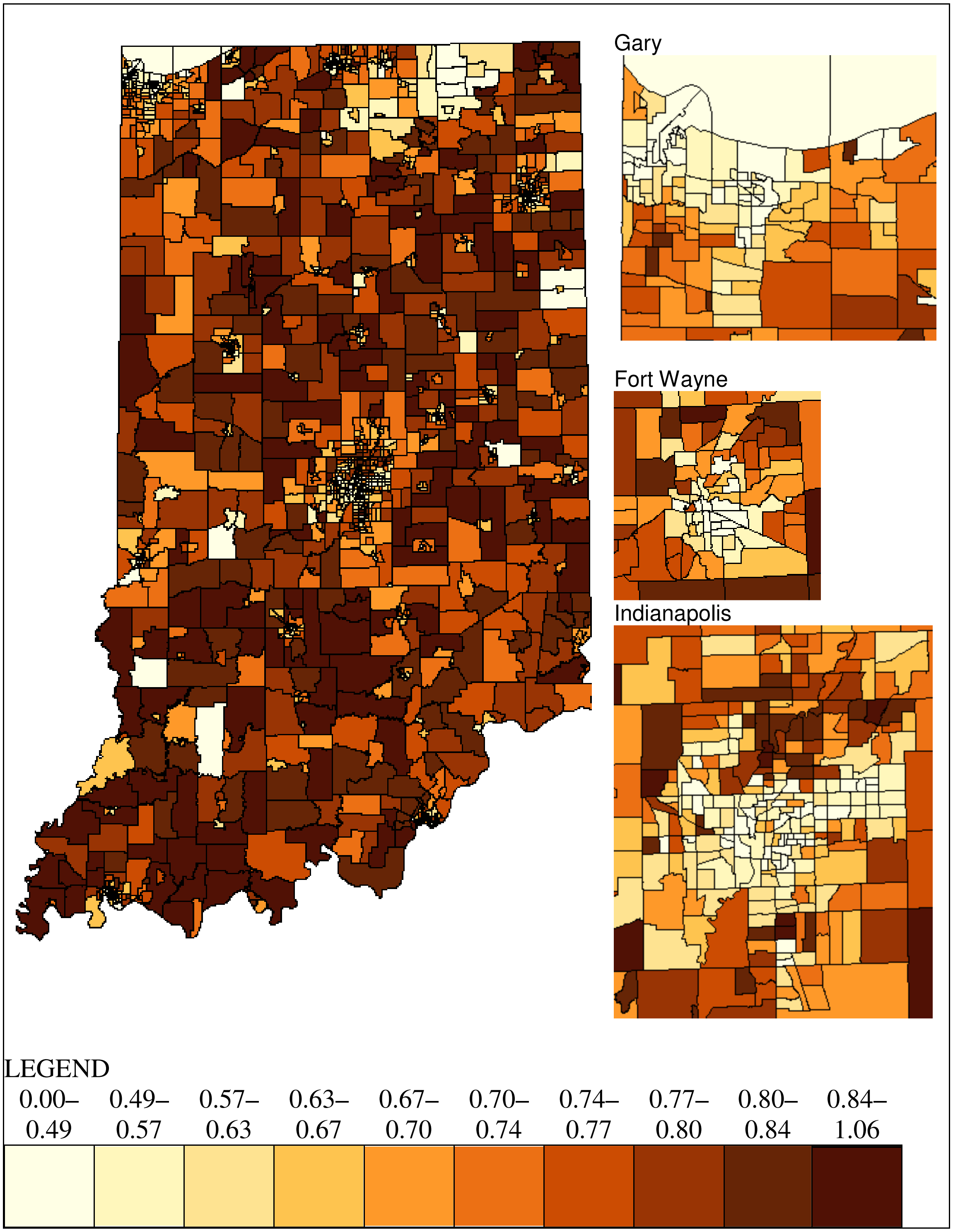


Figure 5-8 Vehicles per Capita Map

5.4.2 Moran's I

As discussed previously in Section 5.2.2.1 and 5.3.2 , a scatter plot of the Moran's I for the dependent variable (vehicles per capita) provides an assessment of the spatial autocorrelation in the data. The Moran's I was calculated to be 0.4737 with a corresponding z-score and p-value of 31.21 and 0.001, respectively, and was determined using 999 random permutations. This means the null hypothesis of no spatial autocorrelation is rejected at a 99.9% level of confidence.

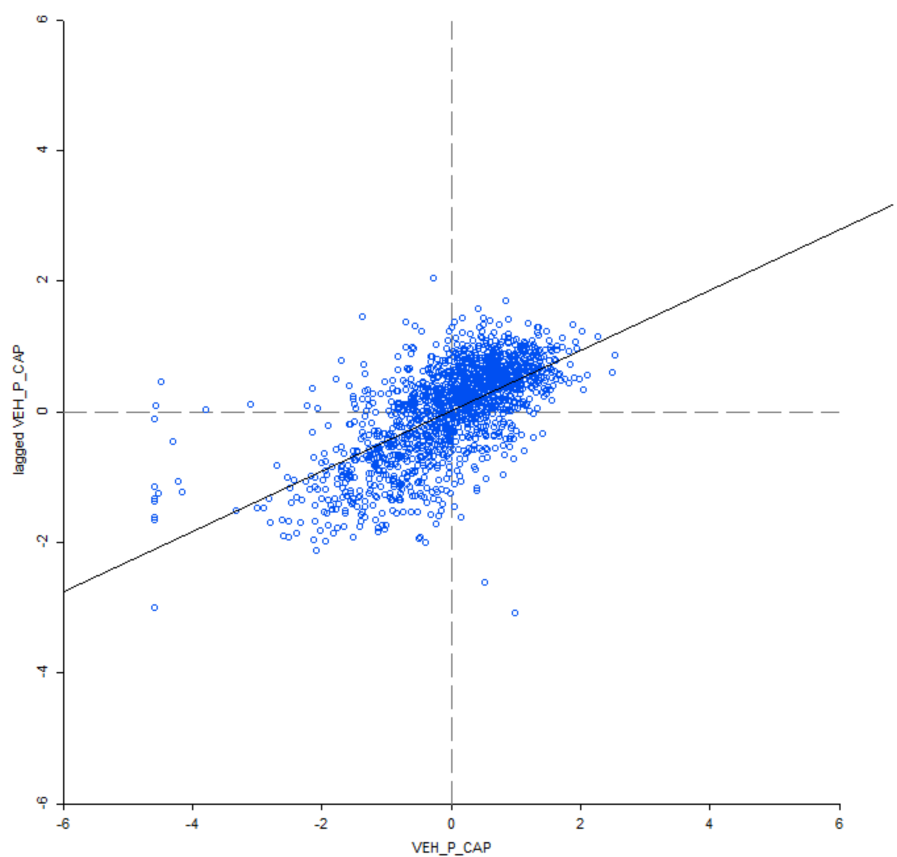


Figure 5-9 Moran's I Scatter Plot for Vehicles per Capita

The LISA cluster map (defined in 5.3.2) is presented in Figure 5-10. Positive autocorrelation is evident in 519 census tracts, compared to only 47 census tracts that experience negative autocorrelation.

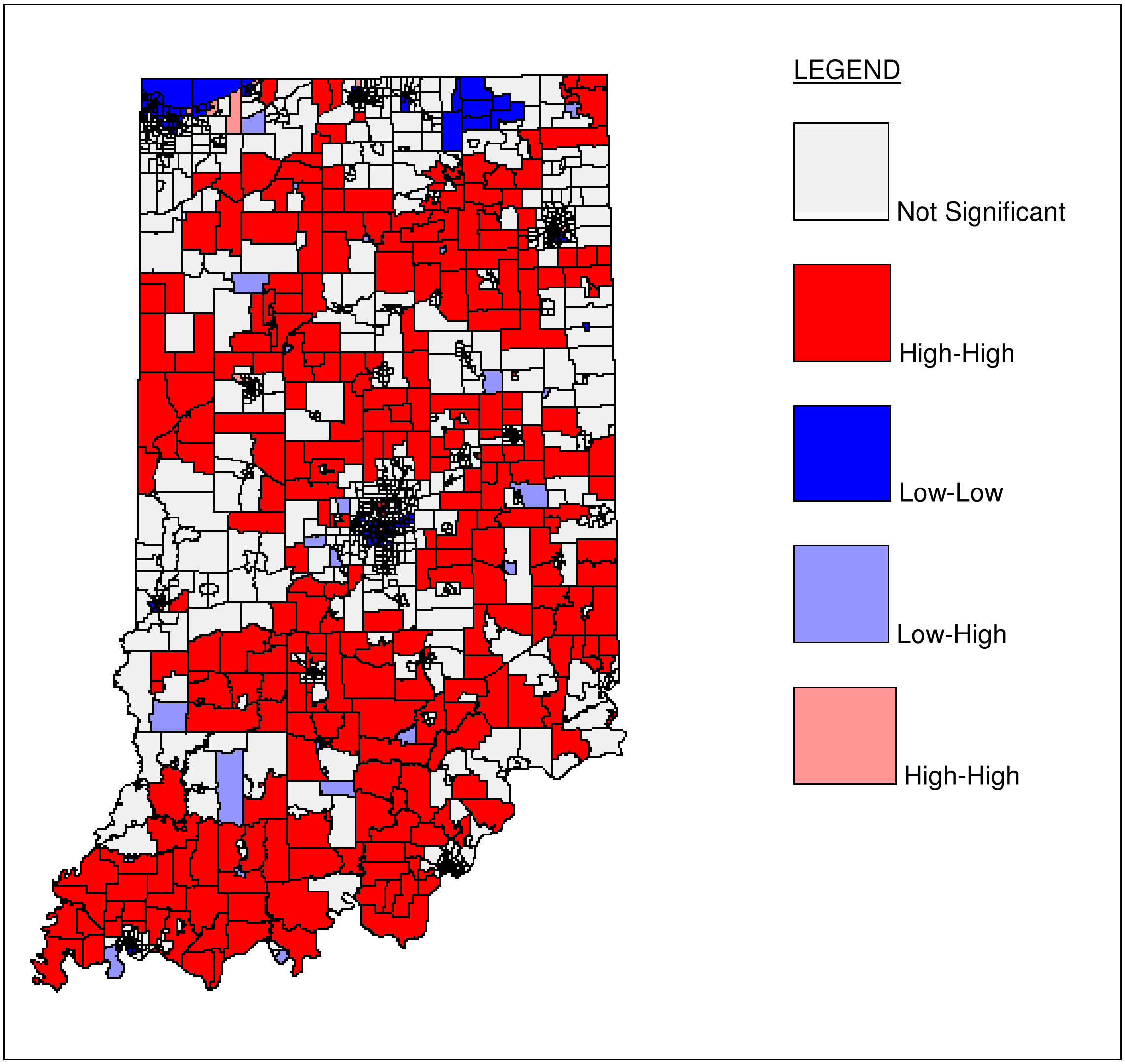


Figure 5-10 LISA Cluster Map for Vehicles per Capita

5.4.3 Aspatial (Non-Spatial) Model Results

The numbers of vehicles per capita was determined to be a function of the population size, average household size, percentage of the population with health insurance, percentage of working population employed in manufacturing, percentage of the population with at least a bachelor's degree, census tract size (in sq miles), percentage of automobiles in the traffic stream, and percentage of single-occupancy commuters. The results of the estimation are presented in Table 5.8, and a detailed discussion of the significant independent variables is presented in the following sections.

The R-squared and adjusted R-squared values indicate the model is explaining 66% of the variance exhibited in the census tract vehicles per capita data. The aspatial OLS model has a multicollinearity number of 42.05. The Koenker–Basset test on the residuals indicated that there was homoscedasticity with a 99% level of confidence (Breusch and Pagan, 1979). To account for this issue, White-adjusted standard errors are used (White, 1980). For a further discussion of the multicollinearity number, Koenker-Basset test, and White-adjusted standard errors, please refer to Section 5.3.3.1 .

Table 5.8 Standard OLS Model Results

Response Variable: Census Tract Vehicles per Capita		
Variable	**Coefficient**	**t-stat**
Constant	-0.034	-1.115
Average HH Size (inhabitants)	-0.0647	-9.342
% Health Ins. (0–100%)	0.0034	9.761
% Labor Force Manufacturing (0–100%)	0.0023	8.189
% Bachelor's Degree (0–100%)	0.0023	11.713
Land Area (sq. mi.)	0.0015	21.058
Population in 1,000s	-0.0072	-5.853
% Auto (0.0–1.0)	-0.111	-3.557
% Single-Occupancy Commuters (0.0–1.0)	0.7221	27.565
Model Statistics		
R-squared	0.6674	
Adjusted R-squared	0.6656	
Number of Observations	1511	
Number of Variables	9	

5.4.4 Model for Spatial Dependence

The Moran's I helped identify the presence of spatial heterogeneity. To help address this issue, spatial regimes were developed for urban and rural census tracts. The results of the urban/rural spatial regime OLS estimation with White-adjusted errors are presented in Table 5.9. Since the spatial lag and spatial error have not been introduced into the modeling framework, the estimated coefficients are the marginal effects.

Table 5.9 Standard OLS Model Results with White-Adjusted Standard Errors and Spatial Regimes

Response Variable: Census Vehicles per Capita				
	Rural Regime		**Urban Regime**	
Variable	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	0.0242	0.981	0.1532	2.571
Average HH Size (inhabitants)	-0.0622	-4.503	-0.0827	-7.808
Mean HH Inc. in 1,000s (2012 dollars)	0.0023	4.603	0.0016	7.971
% Health Ins. (0–100%)	0.0035	2.215	0.0021	3.455
% Unemployed (0–100%)	-0.0001	-0.085	-0.0036	-6.451
% Labor Force Manuf. (0–100%)	0.0008	1.653	0.0015	4.899
Land Area (sq. mi.)	0.0005	5.290	0.0017	7.601
% CLM on State	-0.0008	-0.042	-0.0574	-2.093
Population in 1,000s	-0.0163	-5.103	-0.0081	-5.689
% Single occ. commuters (0.0–1.0)	0.5998	3.641	0.5845	11.268
Model Statistics				
R-squared	0.7469		0.6410	
Adjusted R-squared	0.7411		0.6380	
Number of Observations	400		1111	
Number of Variables	10		10	

The vehicles per capita was determined to be a factor of the population, census tract size, average household size, mean income, percentage of the population with health insurance, percentage unemployed, percentage of the labor force, percentage of the roadway centerline miles on the state network, and percentage of single-occupancy commuters. All the selected variables were significant at a 95% level of confidence in the urban regime; however, the percentage unemployment, percentage of the labor force employed in manufacturing, and percentage of the roadway centerline miles on the state network were all statistically insignificant in the rural regime. A detailed discussion of the influence of the independent variables is provided in the final model specification section.

The Chow test for significance between the coefficients of the regime regressions (Table 5.3) indicates that the unemployment rate, land area, percentage of roadway centerline miles on the state network, and population are significant at a 90% level of confidence (please refer to Section 5.3.3.1 for further discussion on the Chow test). The remaining variables would not need to be estimated separately for each regime. The global chow test is significant at a 99% level of confidence, supporting the use of the spatial regimes (Chow, 1960).

Table 5.10 Chow Test for Spatial Regimes (Vehicles per Capita Model)

Variable	**DF**	**Value**	**Probability**
Constant	1	3.999	0.046
Average HH Size (inhabitants)	1	1.383	0.240
Mean HH Inc. (2012 dollars)	1	1.750	0.186
% Health Insurance (0–100%)	1	0.682	0.409
% Unemployed (0–100%)	1	4.086	0.043
% Labor Force Manufacturing (0–100%)	1	1.632	0.201
Land Area (sq. mi.)	1	22.305	0.000
% CLM on State	1	2.978	0.084
Population	1	5.488	0.019
% Single Occ. Commuters (0.0–1.0)	1	0.008	0.930
Global Test	10	135.038	0.000

5.4.5 Cross-Regressive Terms

Social and economic factors that influence the number of vehicles owned by a person, family, or household were dependent on the characteristics of those individuals. As such, the expectation was that the number of statistically significant cross-regressive variables would be limited. Physical characteristics of the highway infrastructure of adjoining census tracts could impact the need for passenger vehicles. This section investigates the cross-regressive independent variables that could influence the vehicle per capita rate. A cross-regressive OLS model with White-adjusted standard errors and spatial regimes was estimated for the vehicle per capita census tract data (Table 5.11). The cross-regressive independent variables found to be significant in one or more of the regimes were the total number of households, average household size, household density, percentage of the labor force in construction, percentage of the labor force in manufacturing, percentage of the centerline miles on the local network, and percentage of single-occupancy commuters. The intuitiveness of these variables is discussed in Section 5.4.7 .

Table 5.11 Cross-Regressive OLS Model Results with White-Adjusted Standard Errors and Spatial Regimes

Response Variable: Census Tract Vehicles per Capita				
	Rural Regime		**Urban Regime**	
Variable	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	0.0381	0.485	0.198	2.463
Average HH Size (inhabitants)	-0.0592	-3.830	-0.0654	-5.469
Mean HH Income in 1,000s (2012 dollars)	0.0023	5.229	0.0016	7.956
% Health Ins. (0–100%)	0.0042	5.303	0.0017	2.702
% Unemployed (0–100%)	0.0007	0.539	-0.003	-5.398
Land Area (sq. mi.)	0.0004	4.840	0.0014	6.296
Population in 1,000s	-0.0132	-5.032	-0.0084	-5.315
% Single Occupancy Commuters (0.0–1.0)	0.432	4.705	0.5741	10.415
Cross-Regressive Terms				
Total HH in 1,000s	0.0020	1.646	0.0158	2.448
Average HH Size (inhabitants)	-0.0704	-2.365	-0.0725	-4.667
% Labor Force Construction (0–100%)	0.003	1.085	0.0047	3.734
% Labor Force Manufacturing (0–100%)	0.0017	2.169	0.0018	4.121
Household Density in 1,000s (HH/sq. mi.)	-0.1296	-3.395	-0.0202	-2.653
% of CLM on Local Network	-0.0058	-0.157	0.1145	3.183
% Single Occupancy Commuters (0.0–1.0)	0.1898	2.075	-0.0281	-0.457
Model Statistics				
R-squared	0.7711		0.6563	
Adjusted R-squared	0.7628		0.6519	
Number of Observations	400		1111	
Number of Variables	15		15	

5.4.6 Lagrange Multiplier Results for Vehicles per Capita Models

The results of the LM and robust LM tests are presented in Table 5.12 (please refer back to Section 5.2.2.2 and equations 5-4 to 5-7 for a detailed discussion on these tests). The LM tests for spatial lag and spatial error are both significant at the 99.9% level of confidence. Because the LM test for spatial lag is affected by the presence of spatial error (and vice versa), robust LM tests were carried out. The robust LM test for lag was significant at a 90% level of confidence, while the robust LM for error was statistically insignificant. Lastly, the LM for SARMA was significant at a 99% level of confidence. The results of the robust LM tests seem to indicate a Spatial Durbin model may be appropriate; however, the results of the LM SARMA seem to indicate that spatial error is still present and a General Spatial Durbin model may be warranted.

Table 5.12 Lagrange Multiplier Test Results for Spatial Lag and Spatial Error (Vehicles per Capita Model)

Test	**DF**	**Value**	**Probability**
Lagrange Multiplier (lag)	1	15.493	0.0001
Robust LM (lag)	1	2.858	0.0909
Lagrange Multiplier (error)	1	13.346	0.0003
Robust LM (error)	1	0.711	0.3992
Lagrange Multiplier (SARMA)	2	16.203	0.0003

A spatial lag model (without spatial error) was estimated to produce an Anselin-Kelejian test for spatial dependence (Anselin & Kelejian, 1997). The test value was 4.495 for the spatial lag model without spatial regime, which is significant at a 95% level of confidence. The test value was 3.10 and 10.92 for the rural and urban regimes, which are statistically significant at a 90% and 99% level of confidence, respectively. This indicates the presence of spatial error remaining in the urban regime. Therefore, the General Spatial Durbin model, which incorporates spatial lag and error, is best suited for the data. A detailed discussion of the model framework for the General Spatial Durbin is provided in Section 5.2.3.6 .

5.4.7 Final Model Specifications (General Spatial Durbin)

The vehicle per capita dataset was determined to exhibit spatial dependence (lag and cross-regressive) and spatial error. Therefore, a General Spatial Durbin model was determined to be best suited to the data. The final model specification is presented in Table 5.13 and includes a constant term, seven independent variables, six cross-regressive terms, a spatial lag of the dependent variable, and spatial error. Coefficient estimates were found to be significant at a 95% level of confidence, unless otherwise noted.

Six variables were significant in at least one regime but insignificant as cross-regressive terms. An increase in the average household income increases the number of vehicles per capita in both the urban and rural regime, reflecting the additional purchasing power of these tracts. Urban and rural census tracts with a greater percentage of individuals with health insurance also have a greater number of vehicles per capita. An increase in unemployment decreases the number of vehicles per capita in urban tracts but is statistically insignificant in the rural regime. Unemployed members of the labor force may be less likely to own a vehicle (or multiple vehicles) due to decreased disposable income and decreased need. The coefficient for the size of the census tract (in square miles) was significant and positive in both regimes. Individuals who live in larger census tracts may need to travel further for work and social activities, decreasing the ability of family members to share an automobile. Likewise, the coefficient for the percentage of single-occupancy commuters was positive and significant in both regimes, reflecting the need for these individuals to have their own personal vehicle. Lastly, as the population of a rural or urban census tract increases, the expected number of vehicles per capita decreases. This may reflect an increased number of family and friends living within proximity, allowing for vehicle and trip sharing.

Only the average household size is significant as both a variable and cross-regressive term. In both urban and rural areas, an increase in household size decreases the expected number of vehicles per capita. This is a logical conclusion, as it reflects the propensity of households with a greater number of people to include a greater number of individuals who cannot drive, specifically children.

The number and density of households were significant cross-regressive terms in both regimes. The number of households in the census tract had positive coefficient, whereas household density had a negative coefficient. An increased household density of neighboring tracts may indicate the presence of accessible alternative transportation sources, such as bus or rail. The coefficient for the percentage of jobs in construction was positive as a cross-regressive term in the urban tracts, but insignificant in the rural census tracts. The coefficient for the percentage of jobs in manufacturing was positive and significant as a cross-regressive term in both regimes. These variables indicate the need for individuals in these fields to have personal transportation to work, possibly as a requirement for their jobs. Lastly, the percentage of roadway miles on the local network was positive and significant in the urban regime. Local roads typically have lower traffic volumes compared to state roads, thus providing a higher level of service. Owning a passenger vehicle for use in commuting and personal trips may seem more attractive to individuals if the sourcing area has a higher percentage of local roads and thus a lower possibility for congestion.

Lastly, the coefficient for spatial lagged dependent variable (vehicles per capita) was positive and significant in the rural regime. This may reflect a driving and vehicle ownership culture more prevalent in the rural areas. The error coefficient (lambda) was significant in both regimes. The model showed good statistical fit with spatial pseudo R-squared values of 0.7703 and 0.6558 for the rural and urban census tract regimes, respectively.

Table 5.13 General Spatial Durbin Model Results with Cross-Regressive Terms and Spatial Regimes

Response Variable: Census Tract Vehicles per Capita				
	Rural Regime		**Urban Regime**	
Variable	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	0.0737	1.202	0.2087	3.806
Average HH Size (inhabitants)	-0.0695	-4.238	-0.0664	-8.050
Mean HH Income in 1,000s (2012 dollars)	0.0023	5.783	0.0017	11.158
% Health Ins. (0–100%)	0.0034	4.592	0.0015	3.693
% Unemployed (0–100%)	0.0005	0.412	-0.003	-6.164
Land Area (sq. mi.)	0.0004	4.496	0.0013	4.685
Population in 1,000s	-0.0129	-4.875	-0.0081	-5.884
% Single-Occupancy Commuter (0.0–1.0)	0.4459	7.068	0.5759	21.218
Cross-Regressive Terms				
Total HH in 1,000s	0.0242	1.953	0.0106	1.634
Average HH Size (inhabitants)	-0.0542	-1.763	-0.0691	-5.047
% Labor Force Construction (0–100%)	0.0029	1.144	0.0041	2.968
% Labor Force Manufacturing (0–100%)	0.0017	2.584	0.0017	3.509
Household Density in 1,000s (HH/sq. mi.)	-0.1370	-5.208	-0.0206	-3.010
% CLM on Local Network	0.0080	0.232	0.1041	2.790
Lagged Dependent Variable				
Vehicles per Capita	0.1923	2.499	-0.0129	-0.634
Spatial Error				
Lambda	-0.2139	-1.912	0.1809	3.965
Pseudo R-squared	0.7677		0.6551	
Spatial Pseudo R-squared	0.7703		0.6558	
Number of Observations	400		1111	
Number of Variables	15		15	

5.4.8 Vehicles per Capita Summary

The number of vehicles in a state is an important factor when any agency seeks to estimate the earnings potential of new revenue structure. The numbers of vehicles in each census tract was weighted by the population to yield a value of vehicles per capita. The preceding analysis characterized the social and economic characteristics of a census tract that influences the expected vehicles per capita.

Various aspatial and spatial modeling techniques were implemented to determine the superior model. White-adjusted standard errors were used to correct for heteroskedasticity in the data. Spatial regimes were developed for urban and rural census tracts and were found to be statistically significant using the global Chow test statistic. The cross-regressive terms found to be significant in the spatial regime model were the total number of households, average household size, household density, percentage of the labor force in construction, percentage of the labor force in manufacturing, percentage of roadway miles on the state network, and percentage of single-occupancy commuters. The Lagrange Multiplier test for lag, robust lag, error, and robust error led to the final model specification of a General Spatial Durbin model. The lagged dependent variable was found to be significant at a 95% level of confidence in rural regime but insignificant in the urban regime, while the opposite was true for the spatial error component.

Table 5.14 compares the model statistics for each stage of model development. The results show that goodness-of-fit (adjust R-squared) improved from 0.6656 in the base OLS model to 0.7411 and 0.6380 in the rural and urban regimes. When cross-regressive terms were introduced, the rural and urban adjusted r-squared values improved to 0.7628 and 0.6519, respectively. Lastly, when spatial lag of the dependent variable and spatial error were included in the model, the goodness-of-fit improved to 0.7703 and 0.6558 for the rural and urban regimes, respectively. Model validation is provided in Figure 5.11. The predicted values were compared to the actual per capita vehicle ownership for each census tract with an average of 8.9% deviation from the actual value. This is an improvement over the aspatial model (Table 5.8) which had an average deviation of 10.4%.

Table 5.14 Comparison of Model Statistics

Model	**R^2 / Pseudo R^2**	**Adj. R^2 / Spatial Pseudo R^2**	**# of Obs.**	**# of Var.**
OLS	0.6674	0.6656	1511	9
Rural Regime				
OLS model with Spatial Regimes and White-Adjusted Standard Errors	0.7469	0.7411	400	10
OLS model with Spatial Regimes, White-Adjusted Standard Errors, and Cross-Regressive Terms	0.7711	0.7628	400	15
General Spatial Durbin Model with Cross-Regressive Terms and Spatial Regimes	0.7677	0.7703	400	15
Urban Regime				
OLS model with Spatial Regimes and White-Adjusted Standard Errors	0.6410	0.6380	1111	10
OLS model with Spatial Regimes, White-Adjusted Standard Errors, and Cross-Regressive Terms	0.6563	0.6519	1111	15
General Spatial Durbin Model with Cross-Regressive Terms and Spatial Regimes	0.6551	0.6558	1111	15

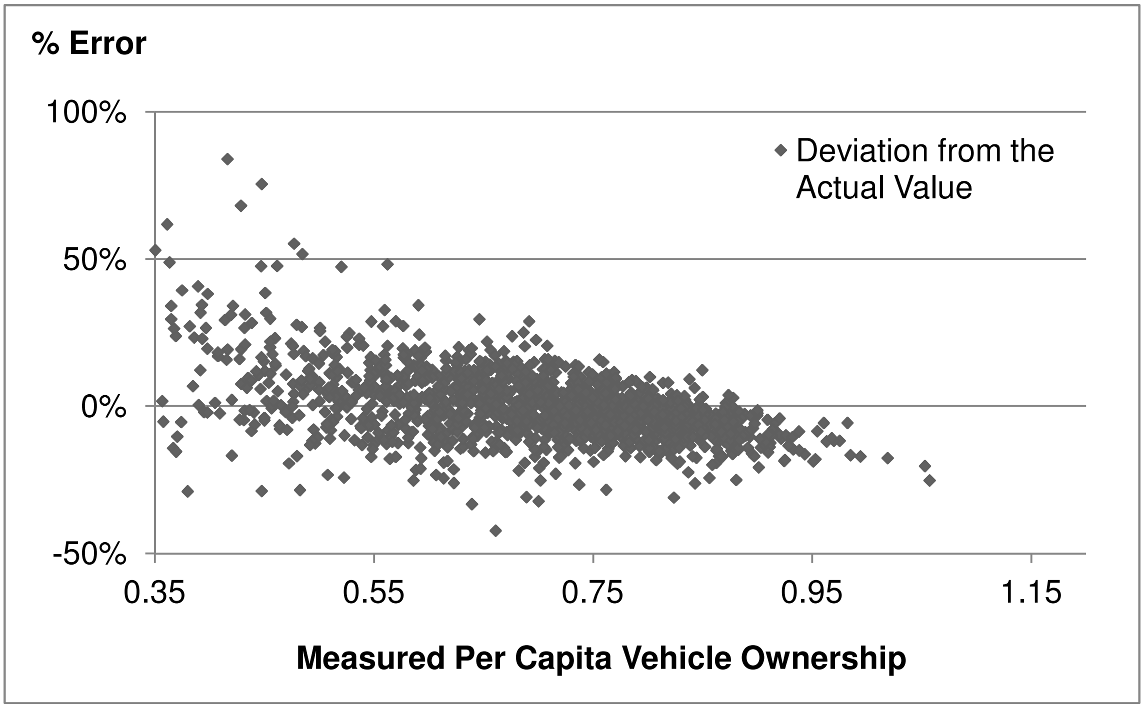


Figure 5.11 Per Capita Vehicle Ownership Model Validation

5.5 Spatial Analysis Summary

The current chapter detailed the methodology used to the estimate vehicle use and ownership as a function of census tract socioeconomic data. The model that best accounted for the underlying spatial trends in the vehicle use data (VMT/M) was a Spatial Durbin model because the data exhibited spatial lag but not spatial error. The spatial model for vehicle ownership (vehicles per capita) experienced both spatial lag and spatial error. To account for these factors, a General Spatial Durbin model with urban/rural regimes was used to estimate the average number of vehicles per capita for each census tract as function socioeconomic data.

Therefore the sensitivity to a 1% change in each explanatory variable was determined using progressive iterations of the estimated model. The final results are presented in Table 5.15. These results are presented in detail in Chapter 6.

Table 5.15 Elasticity of Vehicle Use and Ownership

	VMT/M					Vehicles per Capita				
Factor (1% Increase)	Ind. Var.	Lagged Ind. Var.	Lagged Dep. Var.	% Change	Δ Yearly VMT (M)	Ind. Var.	Lagged Ind. Var.	Lagged Dep. Var.	% Change	Δ Veh. (T)
Population	Y	N	Y	0.093%	65.33	Y	N	Y	0.930%	41.68
Educational Attainment: Bachelor's Degree or Higher (%)	Y	Y	Y	0.141%	99.53	N	N	N	0.000%	0.00
Unemployment (%)	N	Y	Y	0.156%	110.37	Y	N	Y	-0.030%	-1.34
Per Capita Income	Y	N	Y	0.235%	165.76	Y	N	Y	0.168%	7.54
Industry: Manufacturing (%)	Y	N	Y	-0.230%	-162.10	N	Y	Y	0.045%	2.00
Single-Occupancy Commuters (%)	Y	Y	Y	2.260%	1595.49	Y	N	Y	0.660%	29.60
Average Household Size	N	Y	Y	-0.022%	-15.20	Y	Y	Y	-0.493%	-22.12
Health Insurance Coverage (%)	N	Y	Y	-1.229%	-867.40	Y	N	Y	0.246%	11.04
Land Area (sq. mi.)	Y	N	Y	-0.376%	-265.47	Y	N	Y	0.032%	1.42
Number of Households (Total)	N	Y	Y	0.508%	358.52	N	Y	Y	0.035%	1.58
Industry: Construction (%)	N	N	N	0.000%	0.00	N	Y	Y	0.034%	1.51
Household Density	N	Y	Y	0.271%	191.25	N	Y	Y	-0.027%	-1.20
Centerline Miles on Local Network (%)	N	N	N	0.000%	0.00	N	Y	Y	0.104%	4.64
Centerline Miles on State Network (%)	Y	N	Y	0.442%	311.88	N	N	N	0.000%	0.00
Auto VMT (% of total VMT)	Y	N	Y	-2.974%	-2099.82	N	N	N	0.000%	0.00

CHAPTER 6. REVENUE FORECAST AND FUNDING SUSTAINABILITY

6.1 Introduction

In Chapter 3, this dissertation provided a methodology to determine travel characteristics at the census tract-level, and in Chapter 5, it discussed detailed the spatial estimation of census tract vehicle use and ownership using social and economic data. In building upon the results from these chapters, this chapter assesses the impacts of long-term socioeconomic shifts on vehicle use and ownership, and subsequently, revenue generation.

6.2 Inflation and Fuel Economy

In any effort to project revenue generated from highway user taxes and fees, two important factors must be considered: inflation and fuel economy. Inflation is the rise in the cost of goods and services and reflects the general loss of purchasing power over time (BLS, 2014). In the United States, inflation is calculated using the Consumer Price Index (CPI). Forecasting future inflation is difficult over long time horizons; however, the International Monetary Fund (IMF) has projected inflation in the United States to remain near 1.7% per year for the next five years (Figure 6.1). This can be seen as a moderate inflation rate compared to the 2.45% increase in the CPI experienced over the past 20 years (BLS, 2014). For this reason, subsequent analysis in this dissertation uses an inflation rate of 2% unless otherwise noted.

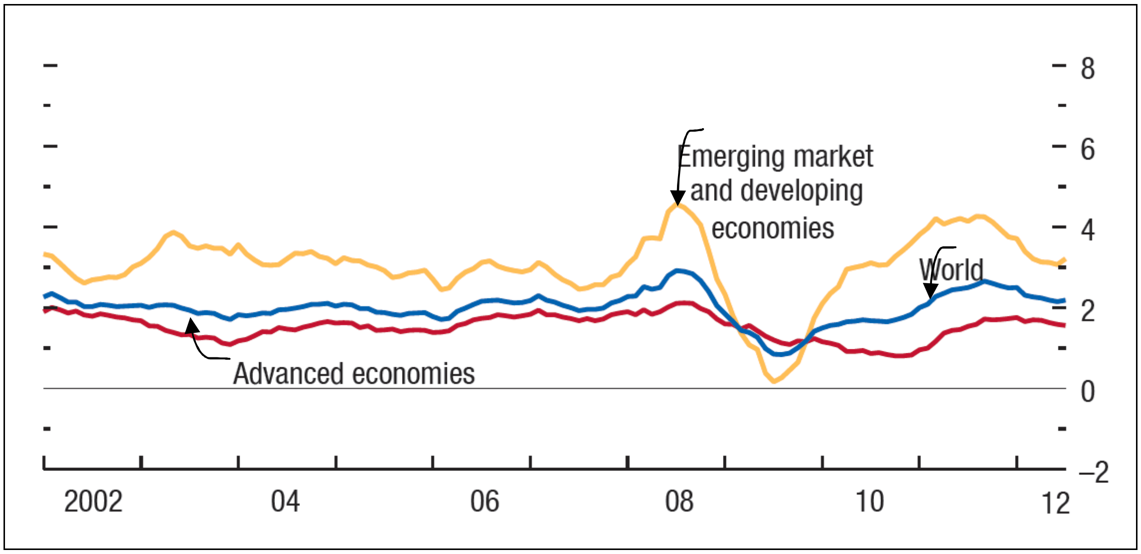


Figure 6.1 Projected Inflation (IMF, 2012)

A detailed discussion on fuel efficiency in the United States and Indiana was presented in Section 3.3 of Chapter 3. As shown in Figure 6.2, the average fuel efficiency for automobiles, SUVs/vans, and heavy-duty trucks (commercial vehicles) currently “on the road” has been increasing at a rate of 0.24, 0.17, and 0.02 gallons per year, respectively (EIA, 2014a). These rates were applied to all revenue analysis subsequently presented in this dissertation (unless otherwise noted).

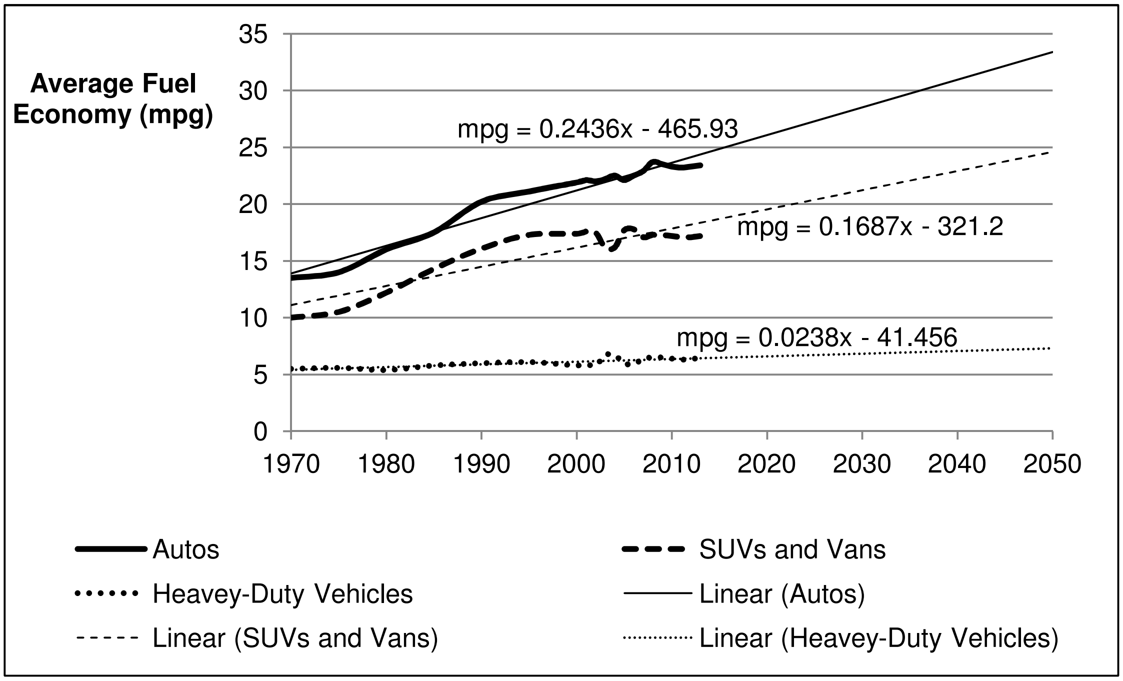


Figure 6.2 Projected Fuel Economy (EIA, 2014a)

The expected fuel tax revenue was calculated as follows:

$$
\begin{aligned}
FTR_i = \; & FTR_{Mi} + FTR_{Ai} + FTR_{SUVi} \\
& = (\%_{\mathrm{M}})(\mathrm{VMT_i})(\%_{\mathrm{M}})(\mathrm{TR})(\mathrm{I_i})\left({}^{1}\!/_{\mathrm{FE_{Mi}}}\right) \\
& + (\%_{\mathrm{A}})(\mathrm{VMT_i})(\%_{\mathrm{A}})(\mathrm{TR})(\mathrm{I_i})\left({}^{1}\!/_{\mathrm{FE_{Ai}}}\right) \\
& + (\%_{\mathrm{SUV}})\,(\mathrm{VMT_i})(\%_{\mathrm{SUV}})(\mathrm{TR})(\mathrm{I_i})({}^{1}\!/_{\mathrm{FE_{SUVi}}})
\end{aligned}
\tag{6-1}
$$

where FTR_i is the Fuel Tax Revenue in year *i*; $\%_M$, $\%_A$, and $\%_{SUV}$ are the percentage of all VMT contributed by motorcycles, autos, and SUVs/vans, respectively; VMT_i is the VMT in year *i* (Chapter 3); *TR* is the fuel tax rate

(\$0.18/gallon); I_i is the net inflation for year i; and FE_{Mi}, FE_{Ai}, and FE_{SUVi}, are the fleet fuel efficiencies for motorcycles, autos, and SUVs/vans, respectively.

Over time, the impact of increased fuel economy and inflation is expected to reduce the annual revenue generated from fuel tax, registration fees, and excise tax, even if the number of vehicles and the annual VMT remain constant over time. Figure 6.3 shows revenue from passenger vehicle fuel sales (motorcycles, autos, and van/SUVs) is projected to decrease by \$216.6 million (41%) and \$350.3 million (66%) by 2030 and 2050, respectively (in 2012 constant dollars). Presenting the data in current dollars effectively removes the impact of inflation, in which case fuel tax revenue would only decrease in response to increased fuel efficiency, decreasing by \$82.1 million and \$147.9 million by 2030 and 2050, respectively (in 2012 constant dollars).

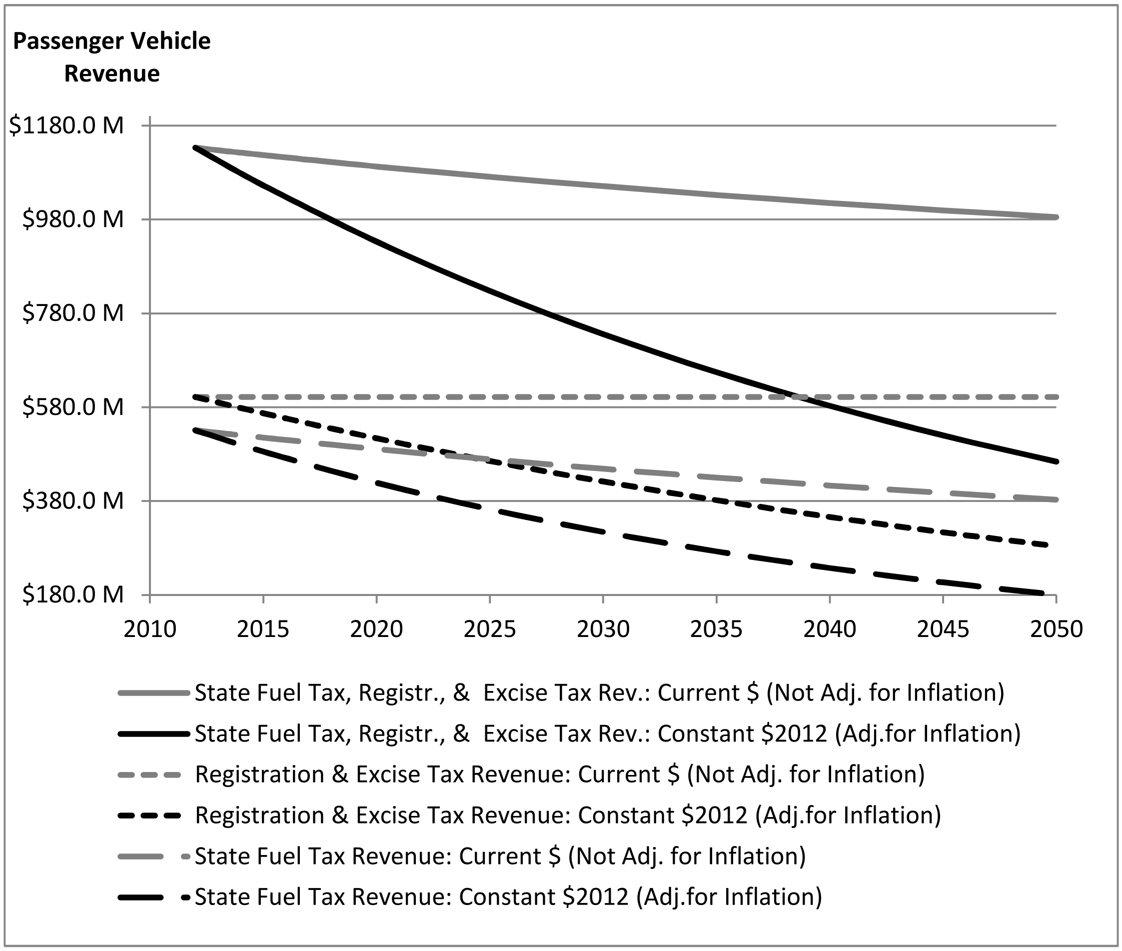


Figure 6.3 Projected Decrease in Revenue from Passenger Vehicle Use and Ownership Due to Inflation and Increasing Fuel Economy

Subsequent analysis in this chapter examines the revenue that is expected to be generated in addition to the revenue presented in Figure 6.3 in response to changing vehicle use and ownership due to long-term socioeconomic demographic shifts. Results are presented in inflation adjusted dollars (constant 2012 dollars) and unadjusted dollars (current dollars).

6.3 Case Study Results

6.3.1 Sensitivity to Population Change

As discussed in Chapter 4, the population in a census tract can increase (or decrease) for two reasons: natural change due to the cumulative effects of births and deaths, and a change due to intra-state or inter-state migration. It is important to investigate the impact of these two trends independently and as a net effect, as the natural population change can be accurately estimated using historical birth and death rates while migration is a reflection of predicted changes in economic and job markets (INDOT, 2013; INDOT, 2013c).

Chapter 4 detailed the forecasted changes in natural, migratory, and net population in Indiana. The increase in the state population is expected to be driven by the natural process of births and deaths, as the majority of the migration is intra-state. However, as explained in Chapter 5, the impact of a change in population on the expected AADT and vehicle ownership is not the same for urban and rural census tracts. Therefore, intra-state migration is expected to have an impact on the projected statewide VMT and vehicle ownership.

6.3.1.1 Population and Annual VMT

The effect of natural, migratory, and net population change on the expected annual VMT for Indiana is presented in Figure 6.4, Figure 6.5, and Figure 6.6, respectively. The shape of the VMT curves closely follows the change in population. Overall, the VMT in 2050 is expected to be 1.67 billion more than in 2012 (an increase of 2.4%). The projected increase in population between 2012 and 2050 is 0.99 million (an increase of 15.3%) (Figure 6.7). The more accelerated rate of population growth compared to vehicle use reflects the projected urbanization of the state. This is because inter-state migration settles at urban areas, and intra-state population shifts out of rural areas.

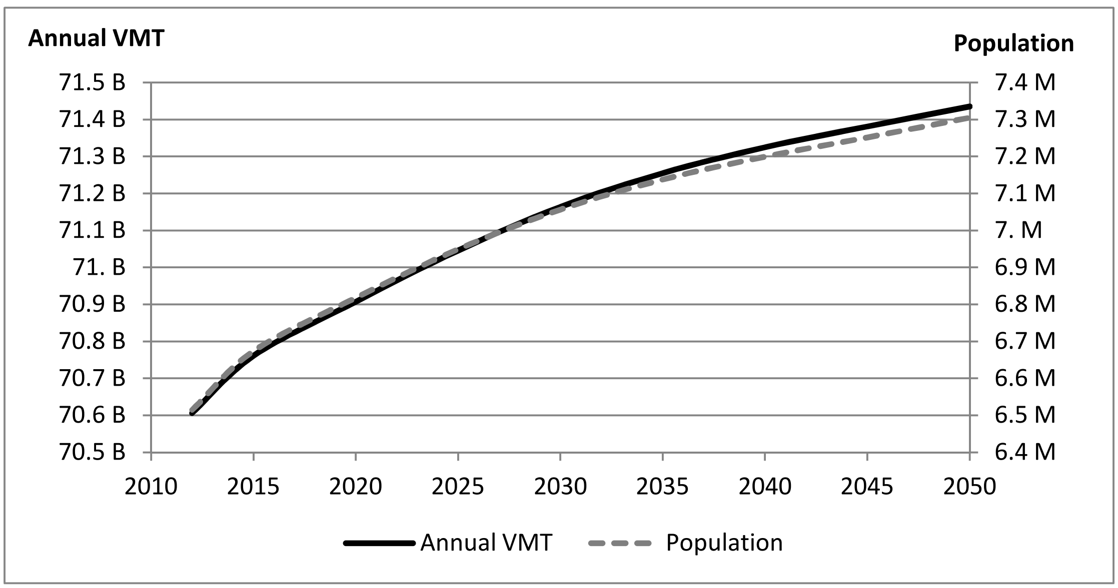


Figure 6.4 VMT Sensitivity to Natural Population Change

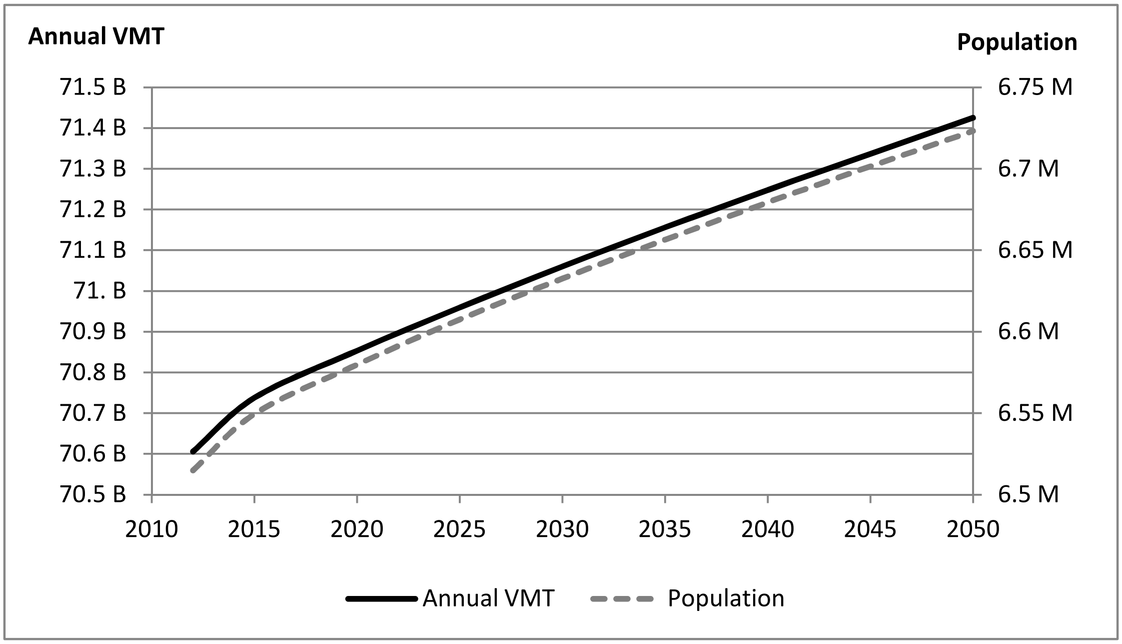


Figure 6.5 VMT Sensitivity to Migratory Population Change

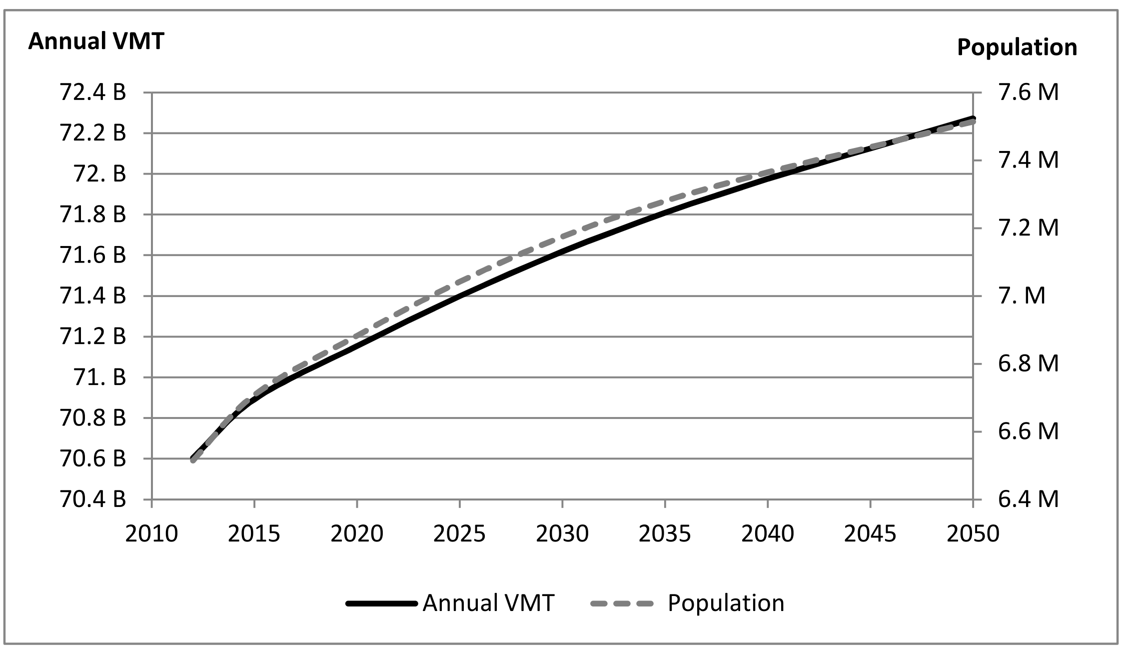


Figure 6.6 VMT Sensitivity to Net Population Change

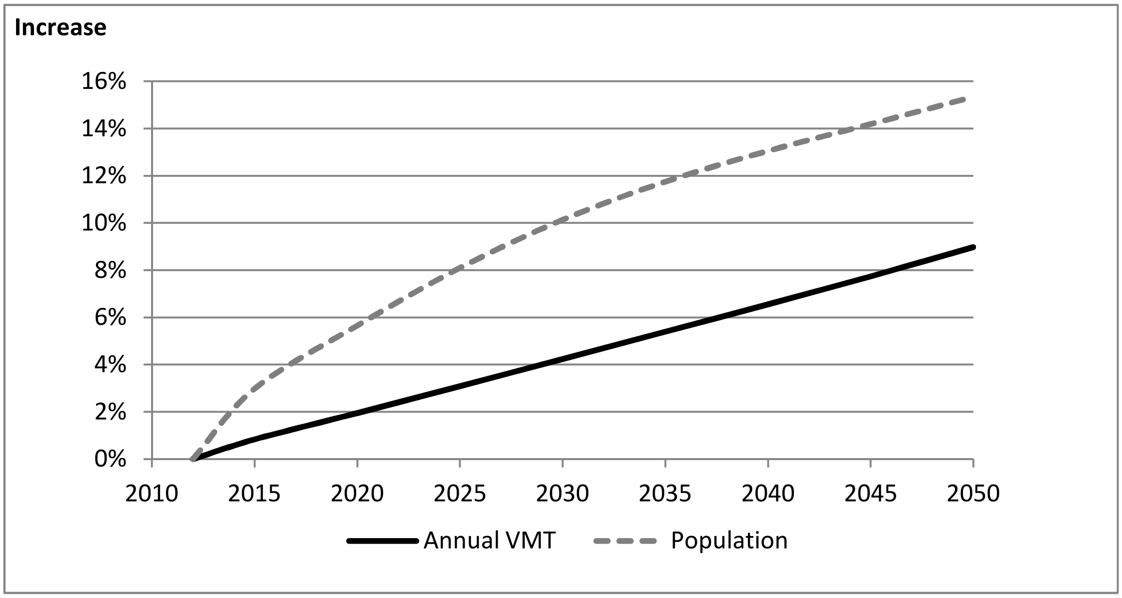


Figure 6.7 VMT and Net Population Growth Rates

6.3.1.2 Population and Vehicle Ownership

Unlike those from usage-based sources, the revenues from vehicle-based sources, such as registration fees, depend not on vehicle usage (VMT) but rather on the number of vehicles registered in the state. Using data from the American Community Survey (U.S. Department of Commerce, 2012), a General Spatial Durbin model was estimated for the number of vehicles per capita (Chapter 5.4). The model results were then applied to the population growth data to determine the change in the number of vehicles in Indiana.

The changes in vehicle ownership due to natural, migratory, and net population increases are presented in Figure 6.8, Figure 6.9, and Figure 6.10, respectively. The increase in Indiana's population between 2012 and 2050 due to natural and migratory factors is expected to be 790,000 and 210,000 respectively. The combined effect is projected to be an increase of 0.99 million. The natural increase in population is expected in both urban and rural areas, whereas an increase in population due to migration is expected predominately in the urban census tracts. The 210,000 increase in population due to migration is projected to result in an additional 140,000 vehicles (a rate of 0.649 vehicles per capita). Overall, the vehicle per capita rate is projected to reduce from 0.688 in 2012 to 0.675 in 2050 due to the net effects of population change.

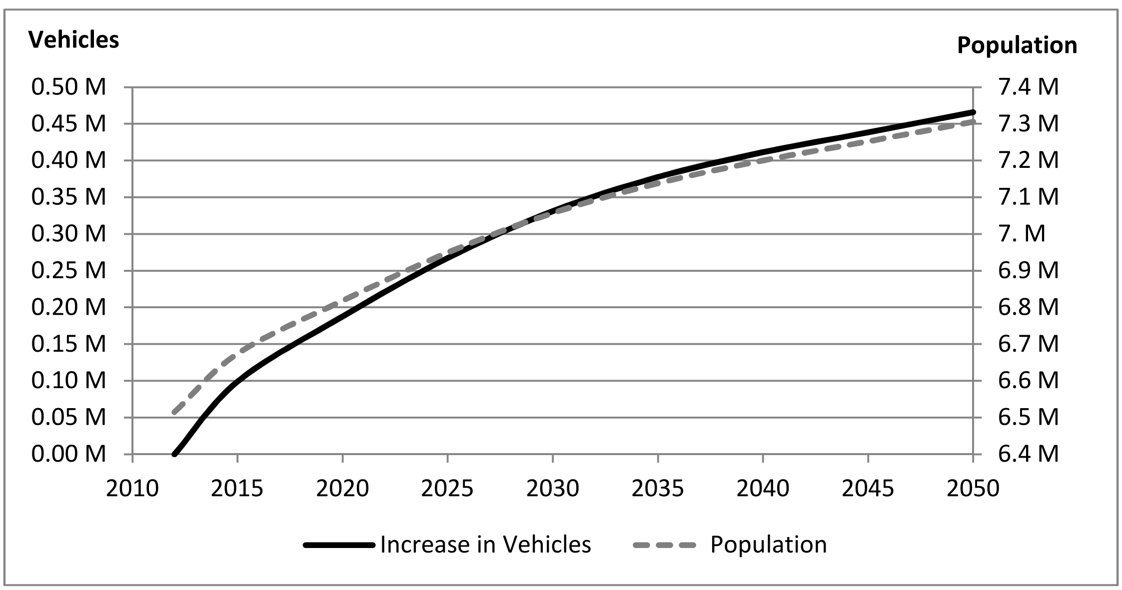


Figure 6.8 Change in Vehicle Ownership Due to Natural Population Change

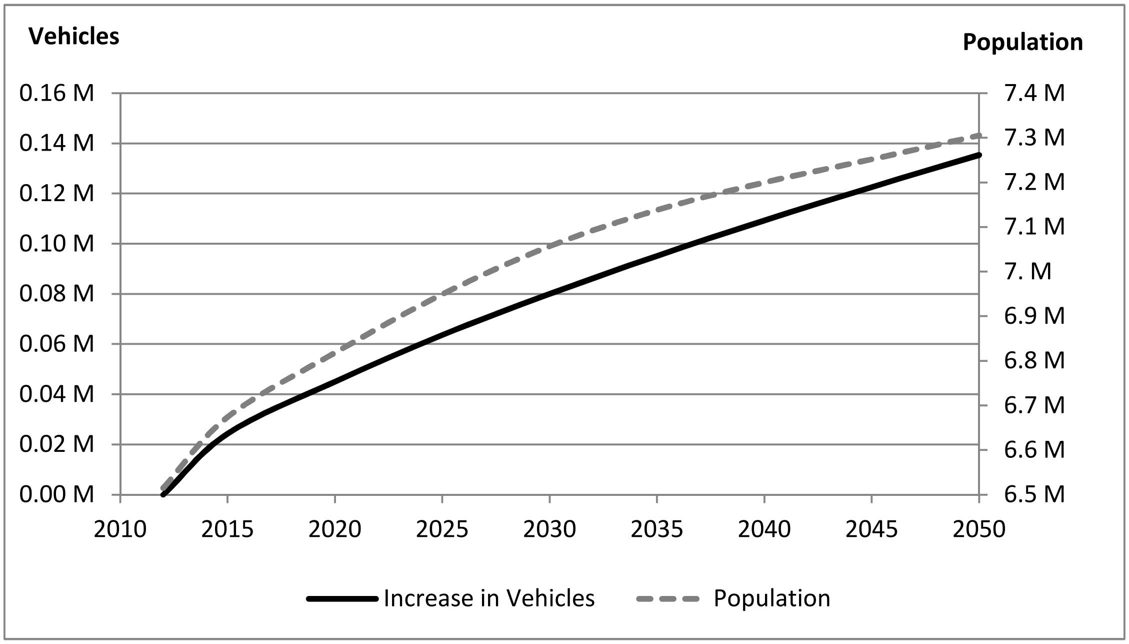


Figure 6.9 Change in Vehicle Ownership Due to Migratory Population Change

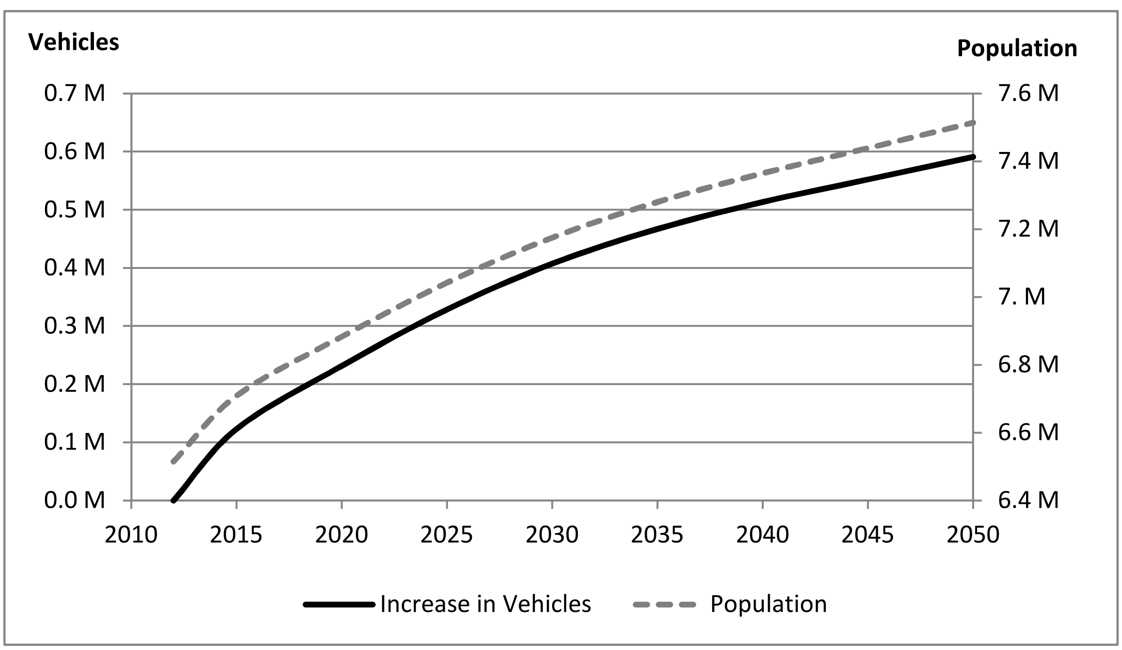


Figure 6.10 Change in Vehicle Ownership Due to Net Population Change

6.3.1.3 Revenue Analysis

The annual revenue generated from passenger vehicles is expected to change in response to the combined effects of inflation, increased fuel economies, and net population change. This is expected to be reflected in the fuel tax revenue generated from vehicle use and the registration fees and excise tax revenue generated from vehicle ownership. Figure 6.11 presents the fuel tax revenue that would be generated between 2012 and 2050 as a result of a net increase in population. Figure 6.12 presents the change in fuel tax revenue due to net population change (the area between the solid and dashed curves in Figure 6.11). Over the course of the study period, the increase in net population is projected to result in an additional $146.2 million in inflation-adjusted revenue (2012 constant dollars), which is equivalent to $228.0 million in unadjusted revenue (currant dollars). However, this increase in overshadowed by the extensive decline in fuel tax revenue to due increased fuel economy and inflation.

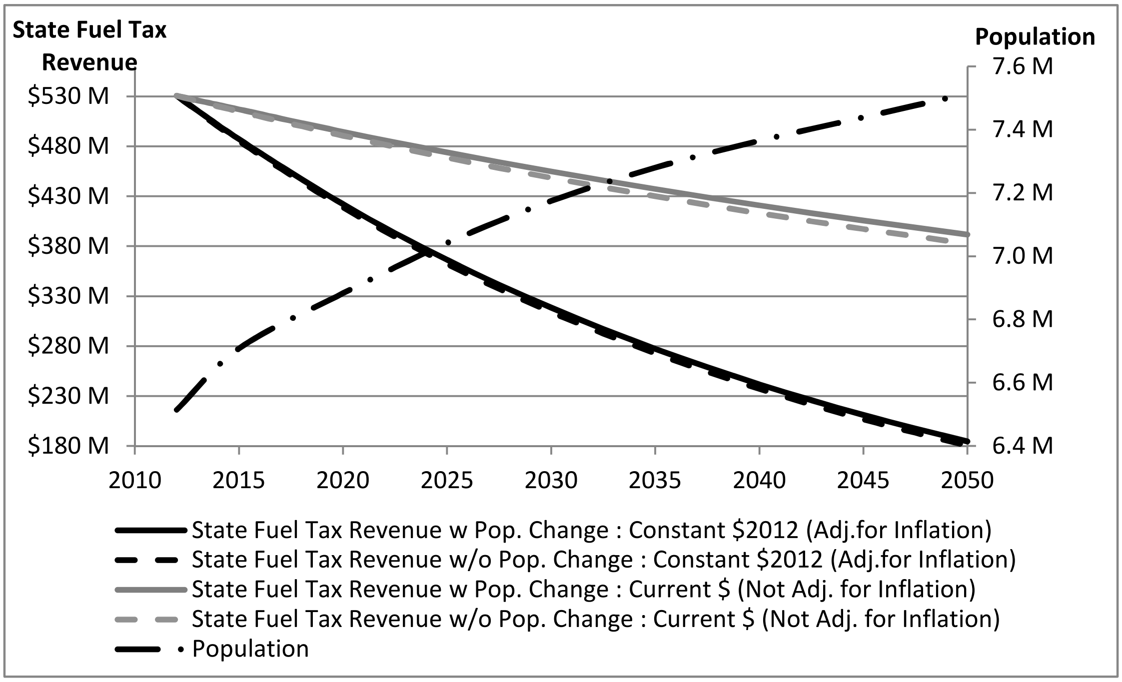


Figure 6.11 State Fuel Tax Revenue from Personal Vehicles Due to Population Shifts

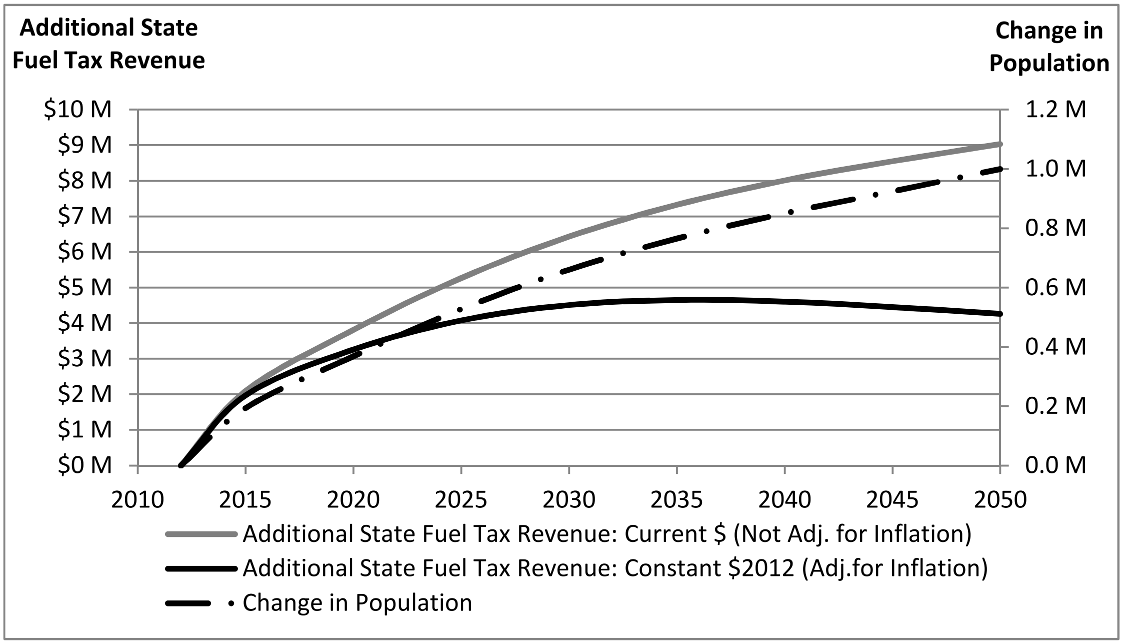


Figure 6.12 Change in State Fuel Tax Revenue Due to Population Shifts

A net increase in population has a more pronounced effect on revenue generated from passenger vehicle registration and excise tax (Figure 6.13). In response to population change, Indiana is projected to see an increase in total annual revenue in current dollars from registration and excise tax, but a decrease in constant dollar revenue. Figure 6.14 presents the additional revenue that is expected to be collected due to population changes.

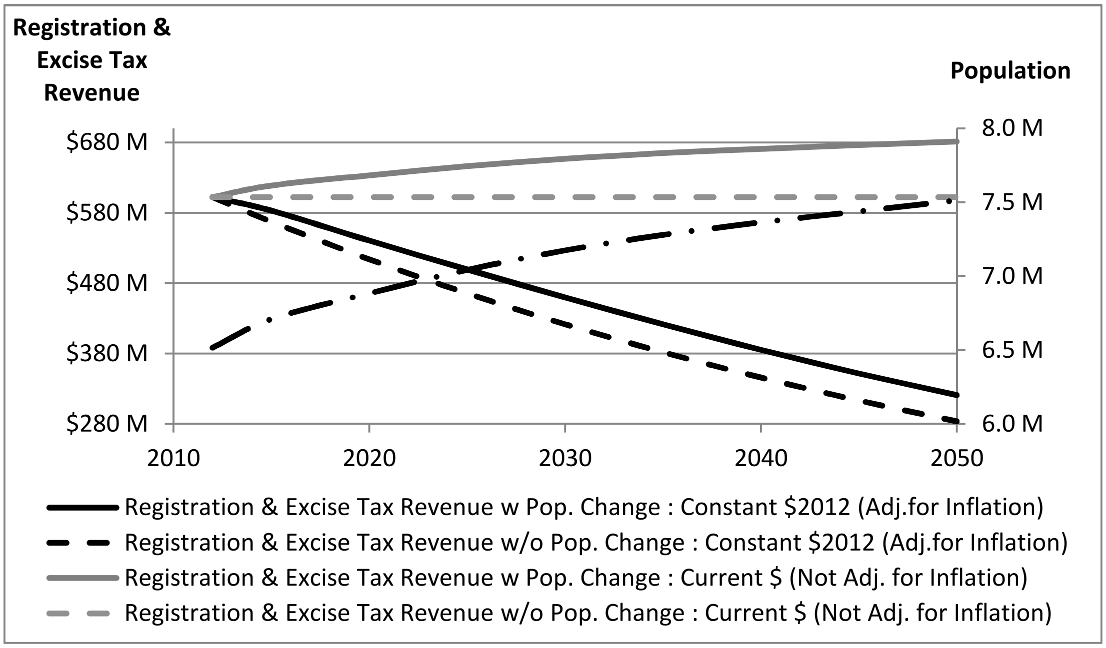


Figure 6.13 Registration and Excise Tax Revenue from Personal Vehicles in Response to Population Shifts

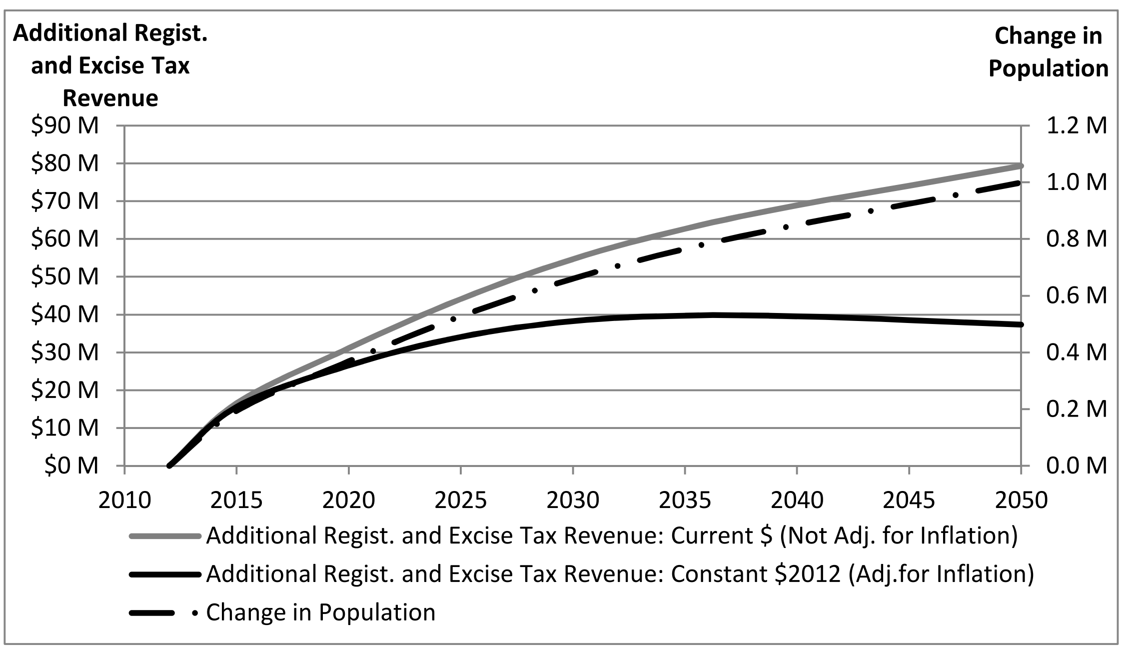


Figure 6.14 Change in Registration and Excise Tax Revenue Due to Population Shifts

Combining the fuel tax analysis with the registration and excise tax analysis produces the net change in expected revenue generated from passenger vehicles as a result of an increase in net population (Figure 6.15). The annual revenue from vehicle fuel taxes, registration fees, and excise taxes is expected to decrease by $59.5 million by 2050 in unadjusted (current) dollars due to the effect of increased fuel economy outpacing the gains from additional miles traveled and number of vehicles. This decrease is increased to $627 million (in 2012 constant dollars) when a 2% annual inflation rate is considered.

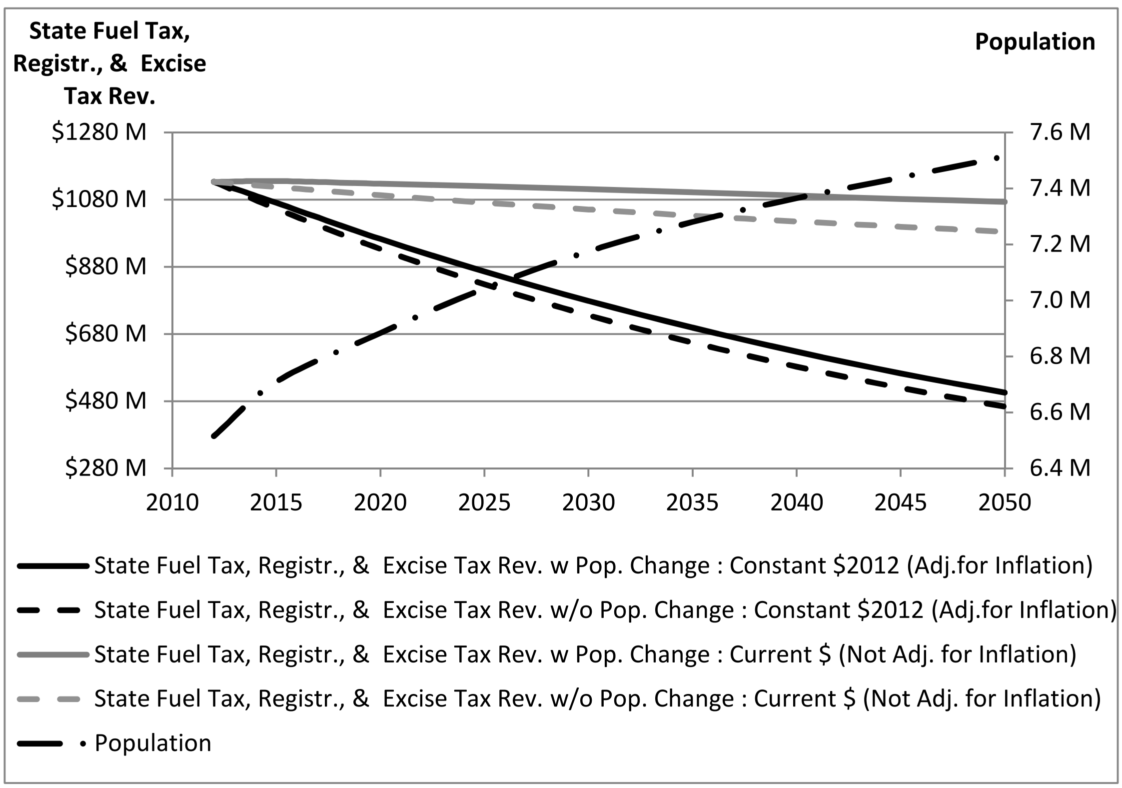


Figure 6.15 State Fuel Tax, Registration, and Excise Tax Revenue from Personal Vehicles

6.3.1.4 Population Change Summary

Population is a driving factor in vehicle use and ownership. A 15% increase in the 2012 net population is expected by 2050. The subsequent increase in passenger vehicle use and ownership is expected to provide additional revenue, but this will not be able to offset the substantial loss in revenue that would result from inflation and increased fuel efficiency, without raising tax rates.

6.3.2 Sensitivity to Educational Attainment

The Spatial Durbin Model in Section 5.3.7 of Chapter 5 showed that vehicle use for a given census tract is influenced by the educational attainment of the tract's residents and its neighbors, specifically the percentage of the population with at least a bachelor's degree. However, it has no impact on the number of vehicles per capita.

6.3.2.1 Education and Annual VMT

Currently, Indiana sits in the bottom 25% of all states when it comes to the percentage of residents with a bachelor's degree or higher. In order to climb into the top 25% of all states, the percentage of inhabitants with a bachelor's degree would have to climb 1% annually. This section determines what impact reaching this goal would have on vehicle use. Figure 6.16 illustrates an expected VMT increase of 4.675 billion miles by 2050 in response to increased educational attainment (not including the 1.67 billion mile increase due to population change).

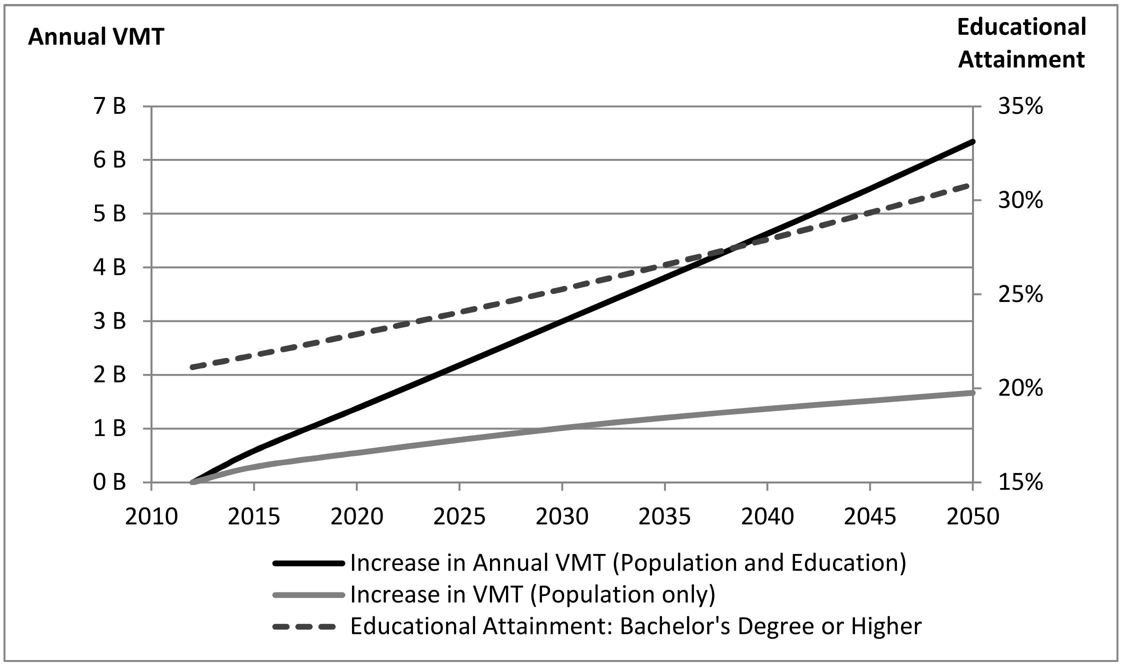


Figure 6.16 Change in VMT Due to Increased Educational Attainment

6.3.2.2 Revenue Analysis

The model results suggest that an increase in the percentage of the population with a bachelor’s degree is expected to significantly increase the annual VMT. However, the long-term impacts of increased fuel efficiency and inflation limit the impact on revenue generation (Figure 6.17). As shown in Figure 6.18, by 2050, an increase in educational attainment as prescribed by this study would be expected to contribute an additional $11.9 million in inflation-adjusted revenue (constant 2012 dollars), not including the additional fuel tax from an increase in population (using the current gas tax rate of $0.18/gallon).

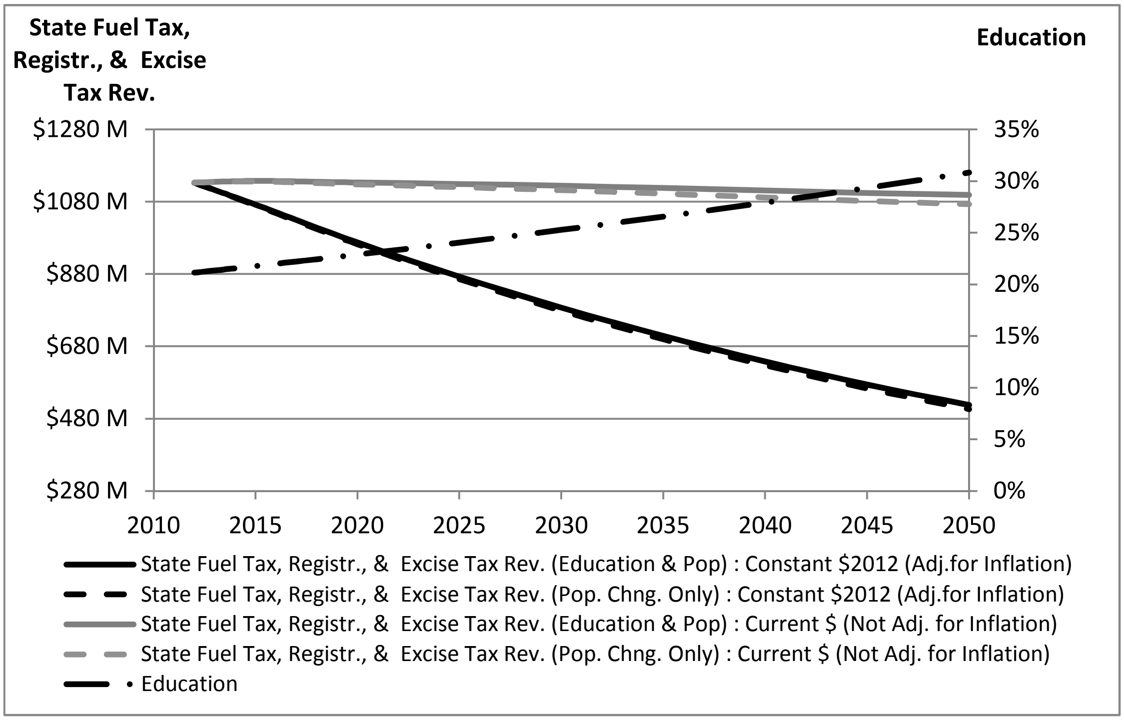


Figure 6.17 State Fuel Tax Revenue from Personal Vehicles

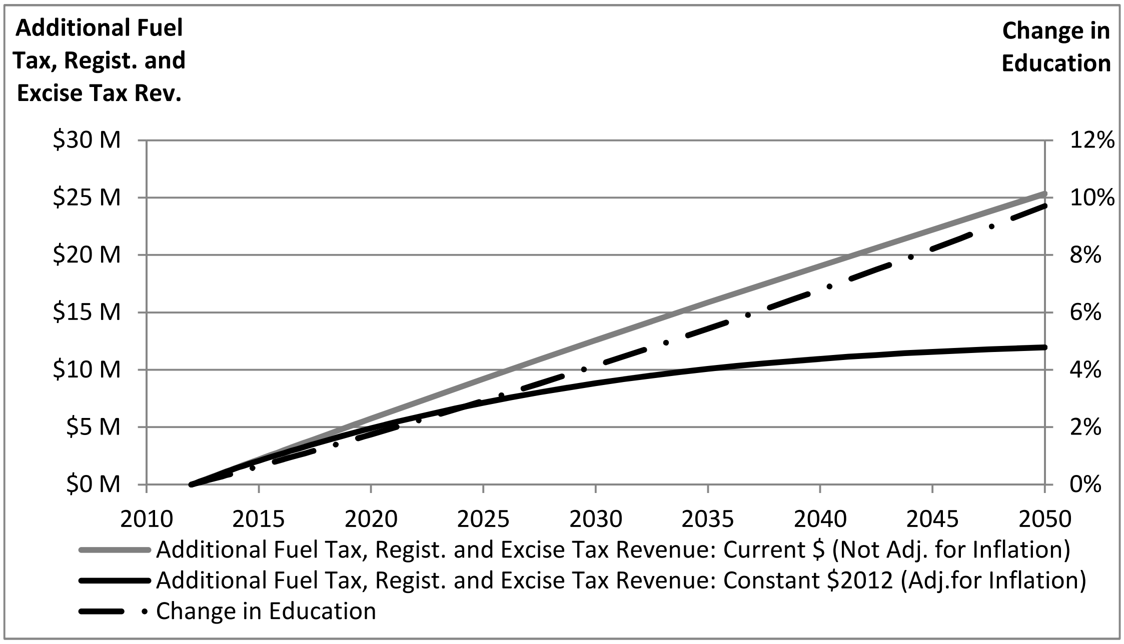


Figure 6.18 Change in State Fuel Tax Revenue Due to Increased Educational Attainment

6.3.2.3 Education Attainment Summary

The percentage of adults with at least a bachelor's degree was found to significantly impact the extent of vehicle use. Currently, Indiana sits in the bottom quarter of all states with an attainment rate of 23.8%. A 1% annual increase between 2012 and 2050 would be needed to obtain a rate equal to the current 3rd quartile of states. This is projected to result in an additional 4.68 billion VMT per year by 2050. The additional VMT is not enough to offset the gas tax losses that would be experienced due to projected inflation and increases in fuel efficiency.

6.3.3 Sensitivity to Unemployment

Unemployment was determined to impact the extent of vehicle use and ownership. This may be plausible because unemployed individuals may need to travel more in search of work and may be less likely to own multiple vehicles. Because the factors that determine a region's unemployment are beyond the scope of this dissertation, this section only investigates the effect of a sustained increase and decrease in unemployment on vehicle use and ownership.

6.3.3.1 Unemployment and Annual VMT

Figure 6.19 and Figure 6.20 show the change in state VMT due to a consistent increase and decrease in the unemployment rate, respectively. A 1% annual increase in unemployment would result in an additional 5.1 billion miles traveled annually by 2050. A 1% decrease reduces annual VMT by 1.8 billion miles by 2050 (this includes the increase in VMT as a result of an increase in population).

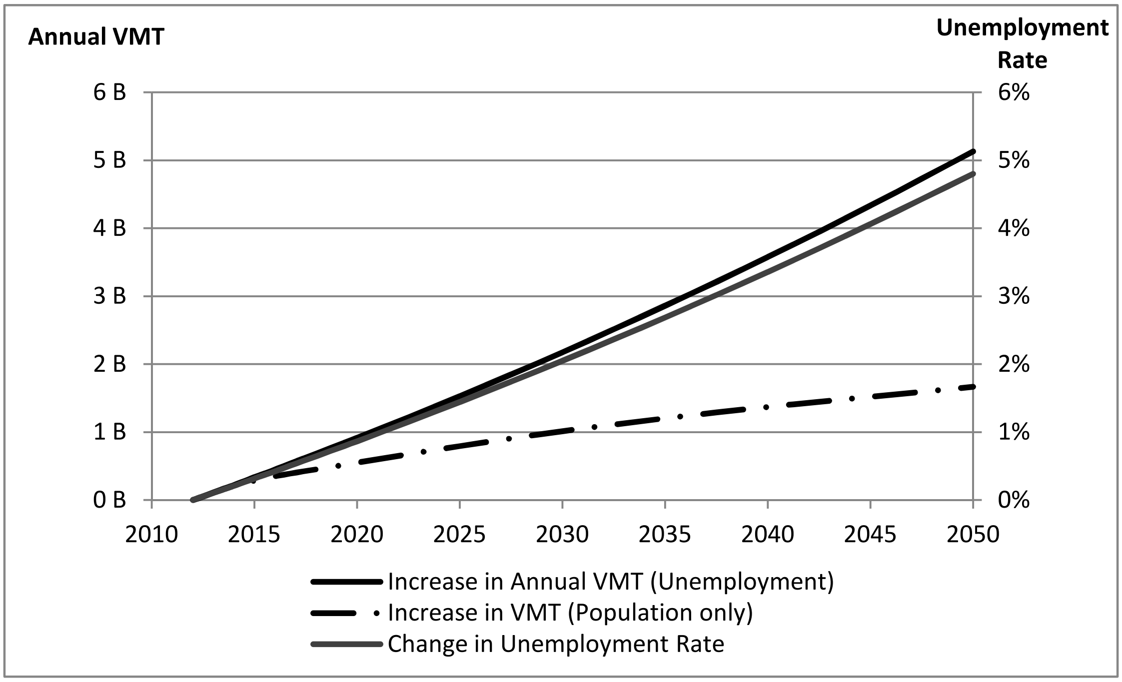


Figure 6.19 Change in VMT Due to an Annual Increase in Unemployment Rate

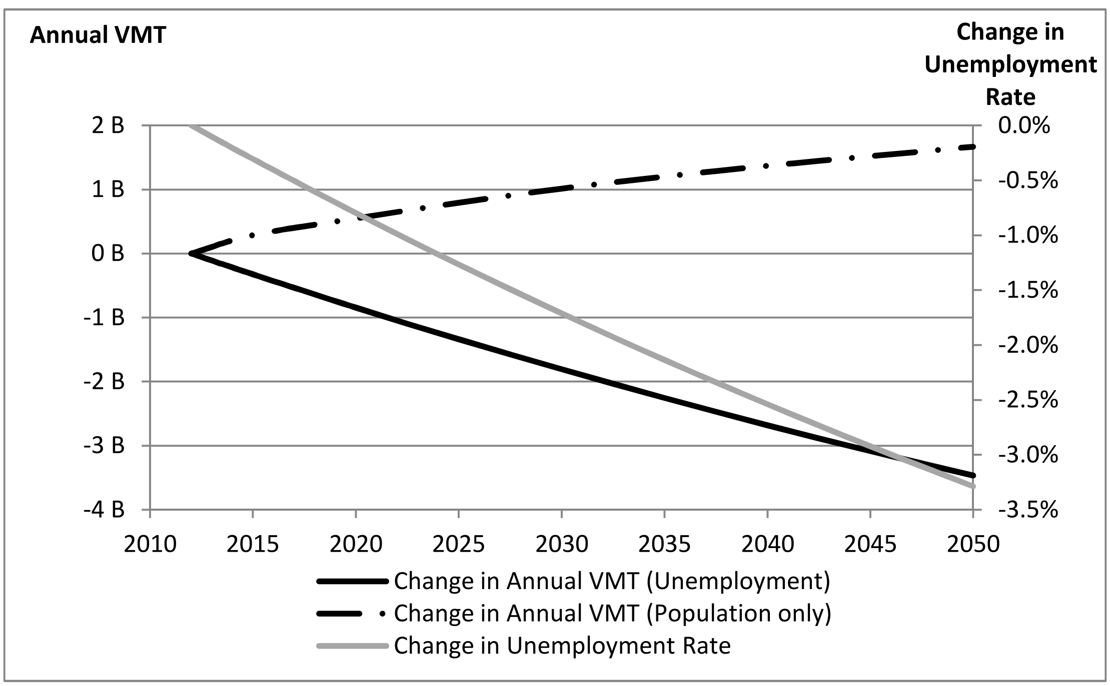


Figure 6.20 Change in VMT Due to an Annual Decrease in Unemployment Rate

6.3.3.2 Unemployment and Vehicle Ownership

Figure 6.21 and Figure 6.22 show the expected change in the number of vehicles in Indiana in response to a sustained increase and decrease in the unemployment rate, respectively. A 1% annual increase in unemployment rate decreases the number of vehicles in the state, as individuals are less able to afford the costs associated with vehicle ownership.

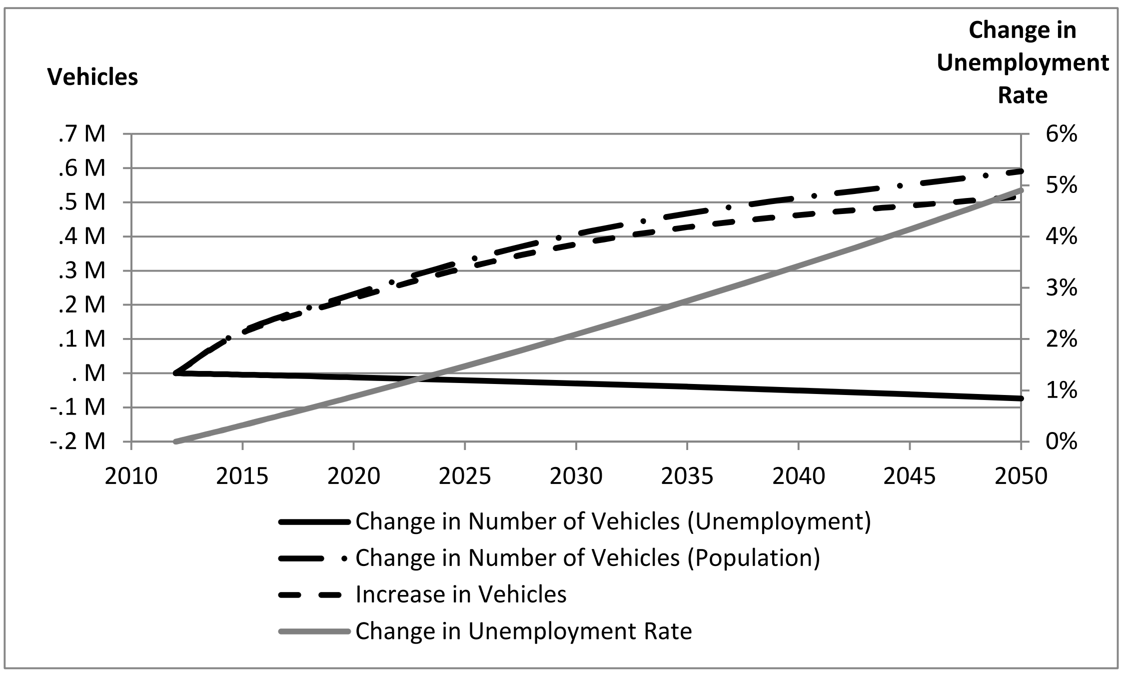


Figure 6.21 Change in Vehicle Ownership Due to Increase in Unemployment

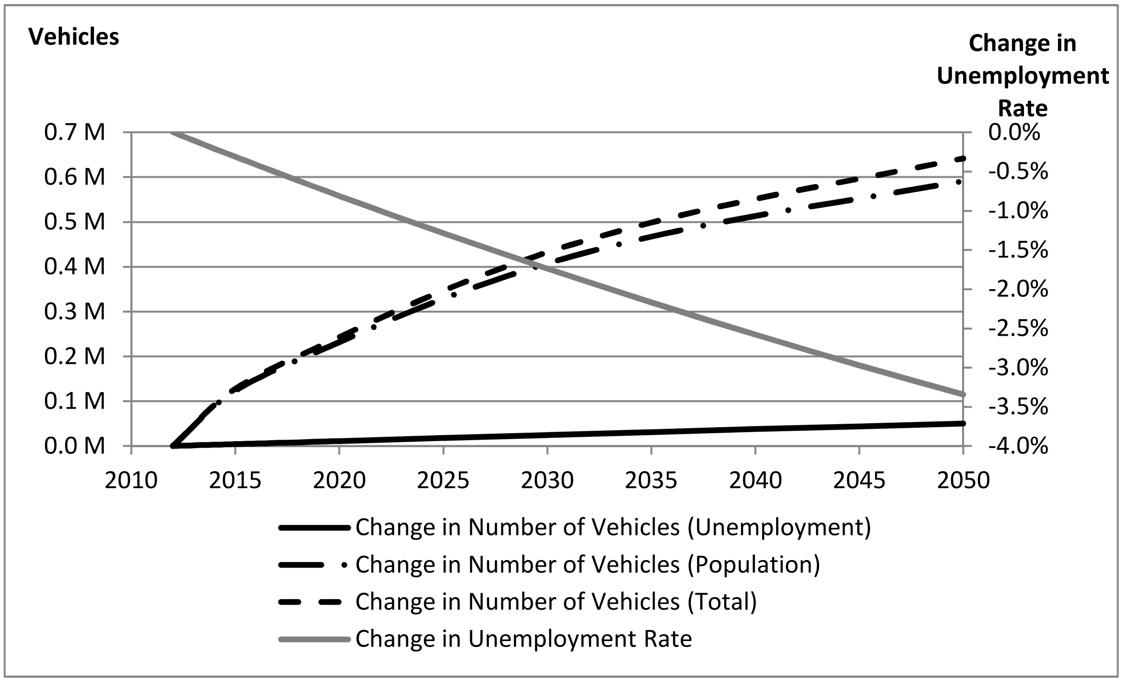


Figure 6.22 Change in Vehicle Ownership Due to Decrease in Unemployment

6.3.3.3 Revenue Analysis

Unemployment and revenue generated from registration and vehicle excise tax is inversely proportional; in other words, a decrease in unemployment would increase revenue generated. Conversely, a decrease in unemployment decreases revenue generated from gasoline tax. A 1% annual decrease in unemployment would reduce annual fuel tax revenue by $8.9 million by 2050 in inflation-adjusted (constant 2012) dollars (Figure 6.23 and Figure 6.24). This loss is increased to $18.8 million in unadjusted (current) dollars. Part of this loss is offset by the $3.2 million (in 2012 dollars) in additional registration fees and excise tax.

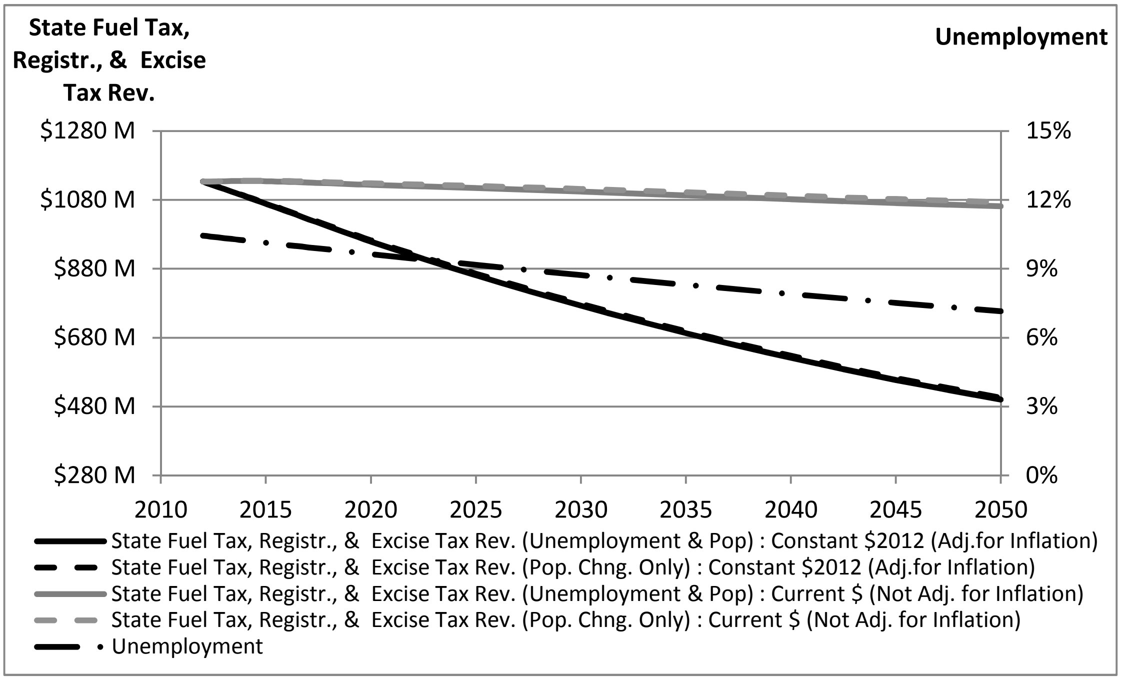


Figure 6.23 State Fuel Tax, Registration, and Excise Tax Revenue from Personal Vehicles

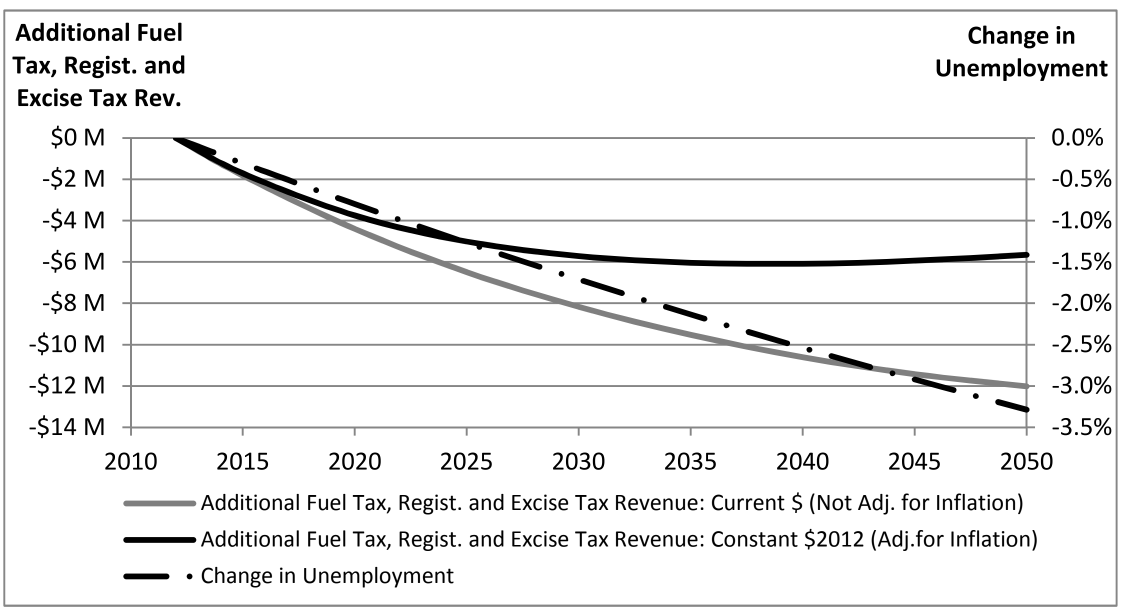


Figure 6.24 Change in State Fuel Tax, Registration, and Excise Tax Revenue Due to Decreased Unemployment

A 1% annual increase in unemployment is expected to result in an additional $13.1 million in annual fuel tax revenue but a reduction of $4.7 million in registration fees and vehicle excise tax, for a net gain of $8.4 million by 2050 (Figure 6.25). The change in revenue caused by a change in unemployment in excess of the change in revenue due to population gains (the area between the dashed and solid curves in Figure 6.25) is presented in Figure 6.26.

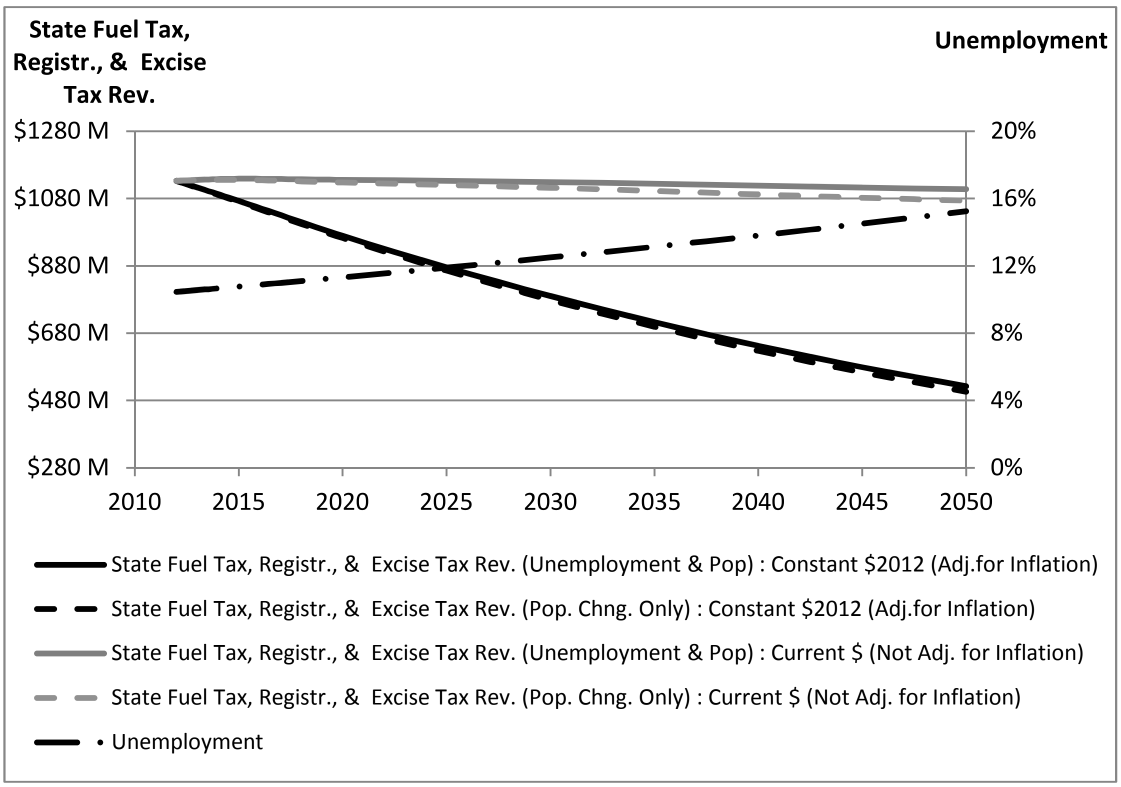


Figure 6.25 State Fuel Tax, Registration, and Excise Tax Revenue from Personal Vehicles

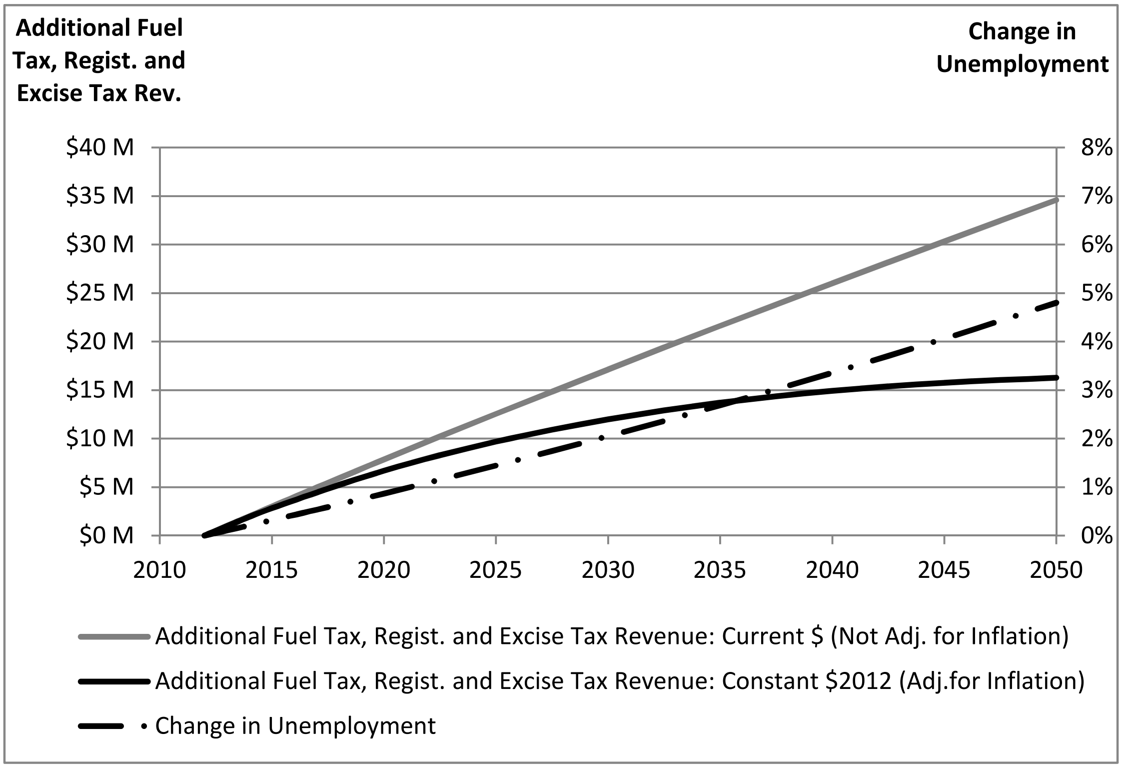


Figure 6.26 Change in State Fuel Tax, Registration, and Excise Tax Revenue Due to Increased Unemployment

6.3.3.4 Unemployment Summary

Unemployment was found to significantly impact the extent of vehicle use and per capita ownership. A sustained 1% annual increase in unemployment would raise the unemployment rate from 10.44% in 2012 to 15.24% in 2050. This would reduce the expected number of vehicles by 70,000. A 1% decrease would result in an unemployment rate of 7.29% by 2050 and is expected add 50,000 vehicles to the state. The 1% annual increase in unemployment is projected increase the annual VMT by 5.13 billion by 2050, not including the additional 1.67 billion VMT expected due to increased population. Reducing the unemployment rate to

7.29% is projected to decrease VMT by 3.47 billion by 2050 (not including the 1.67 billion VMT increase due to net population change). Overall, a reduced (increased) unemployment rate would reduce (increase) the expected revenue. This is because the reduction in VMT is expected to outpace the increase in vehicle ownership.

6.3.4 Sensitivity to Income

Across the United States, a rise in vehicle ownership has been attributed to a rise in per capita income (Dargay et. al., 2007). An increase in personal income makes the population less reliant on public transit and more likely to own at least one vehicle. The model output in Chapter 5 showed that an increase in median or average household income is expected to increase VMT and number of vehicles per capita. Historical records indicate that the annual increase in inflation-adjusted per capita income is approximately 1% in Indiana. The continued effect of this increase is investigated in this section.

6.3.4.1 Income and Annual VMT

Changes in median per capita income across census tracts can be caused by differences in average salaries or average household size. Tracts with similar income per household or per family but with different average household or family size would have a different rate of income per capita. A sharp increase in VMT is expected in response to a 1% annual increase in median household income, with an increase of 8.91 billion VMT by 2050 (Figure 6.27).

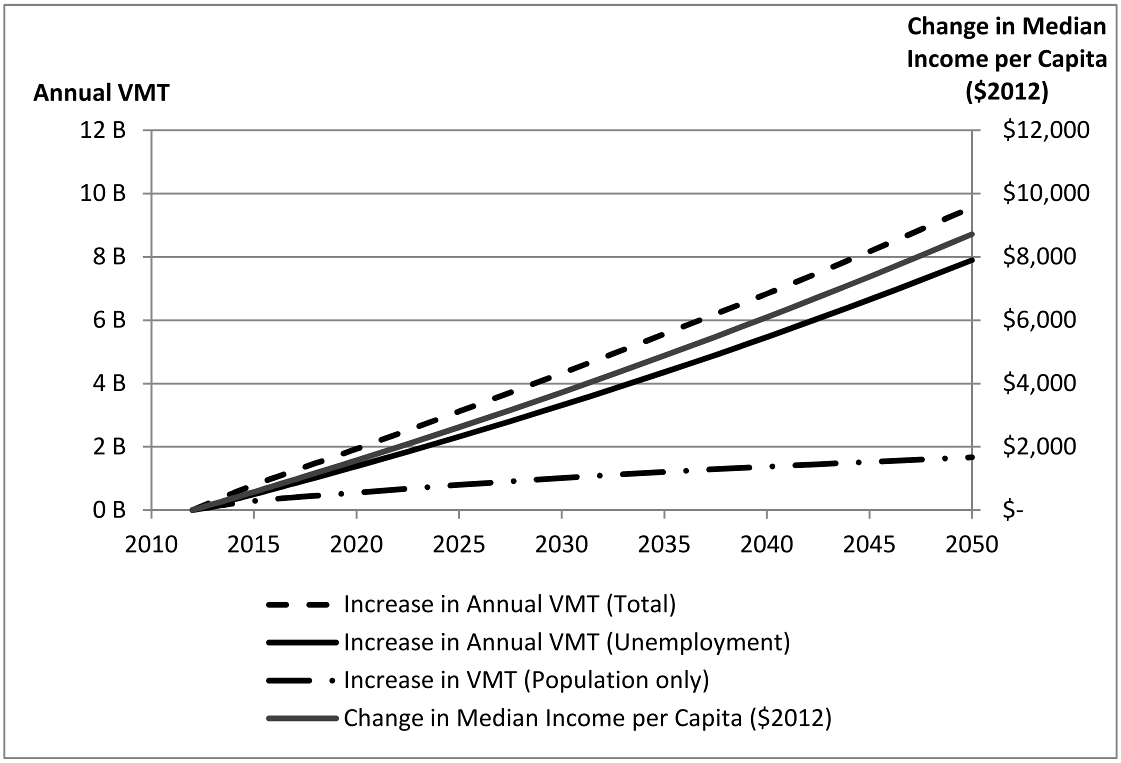


Figure 6.27 Change in VMT Due to an Annual Increase in per Capita Income

6.3.4.2 Income and Vehicle Ownership

Similar to the results from the VMT analysis, a 1% annual increase in average income is expected to significantly increase the number of vehicles in the state. As shown in Figure 6.28, a 1% annual increase in average income is projected to increase the per capita income by $10,712 by 2050 (in inflation-adjusted, constant 2012 dollars). This additional spending power is estimated to add an additional 410,000 vehicles, not including the additional 590,000 vehicles projected as a result of increased population.

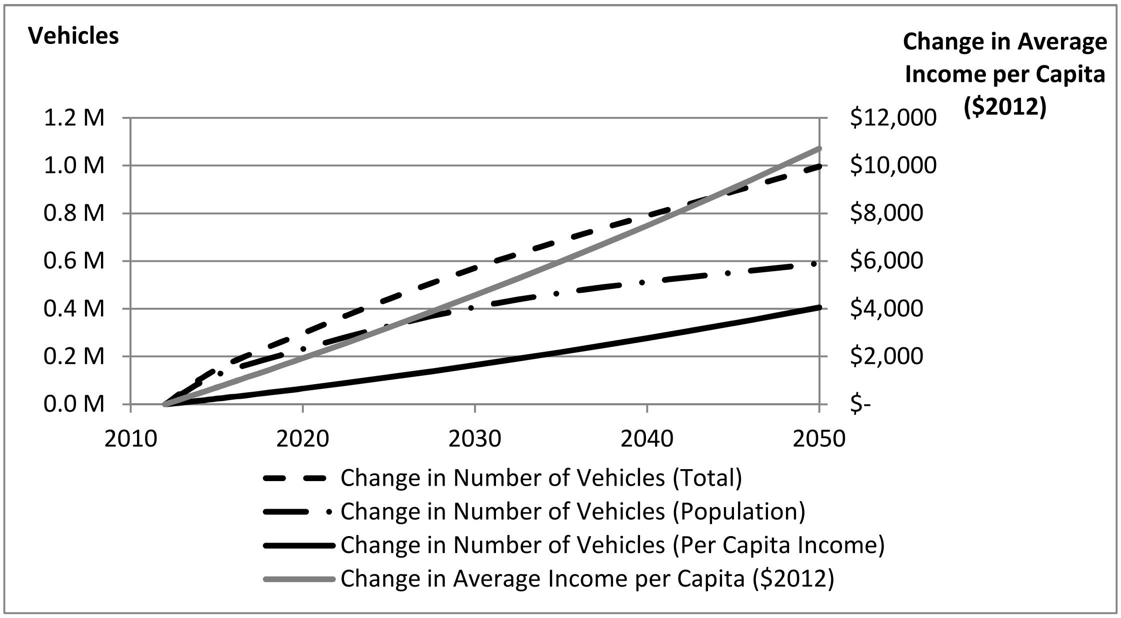


Figure 6.28 Change in Vehicle Ownership Due to Increased Income

6.3.4.3 Revenue Analysis

An increase in income is expected to increase vehicle use and ownership, and therefore increase the revenue generated from fuel taxes, registration fees, and excise taxes. As shown in Figure 6.29 and Figure 6.30, the drastic increase in both VMT and ownership is not enough to offset the losses due to inflation and increased fuel economies. In unadjusted (current) dollars, the total revenue in 2050 is projected to increase by $37.8 million. However, when the revenue is adjusted for inflation, it only results in a projected $581.5 million reduction.

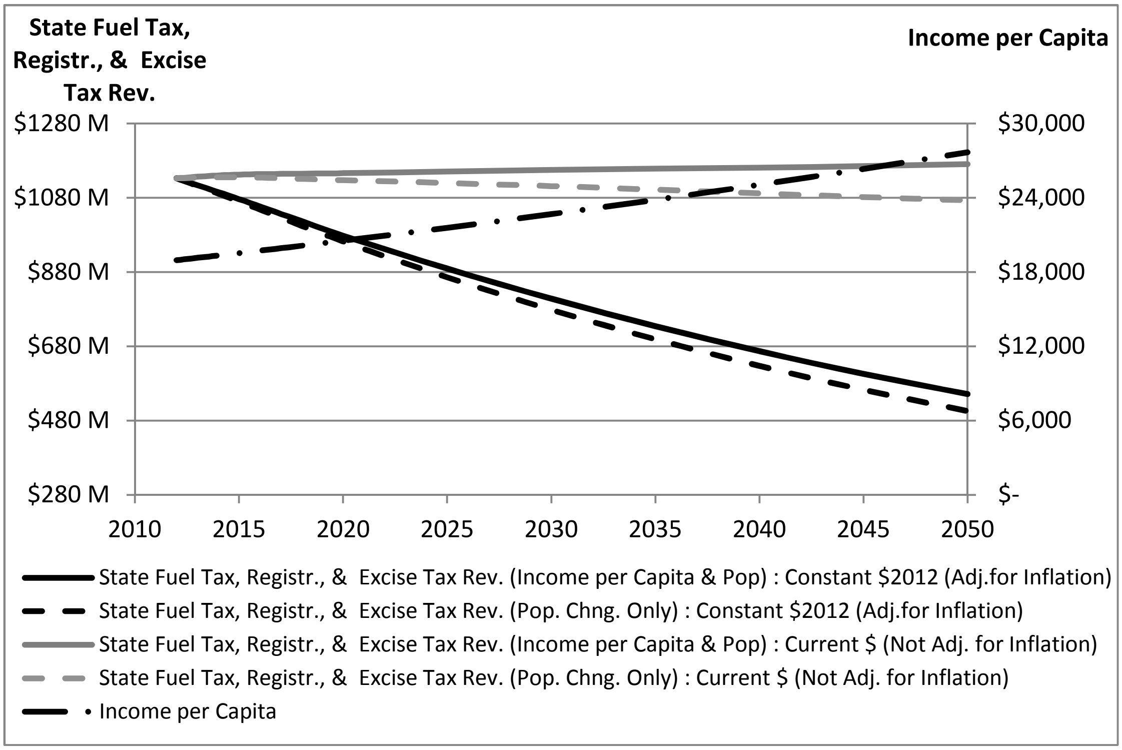


Figure 6.29 State Fuel Tax, Registration, and Excise Tax Revenue from Passenger Vehicles

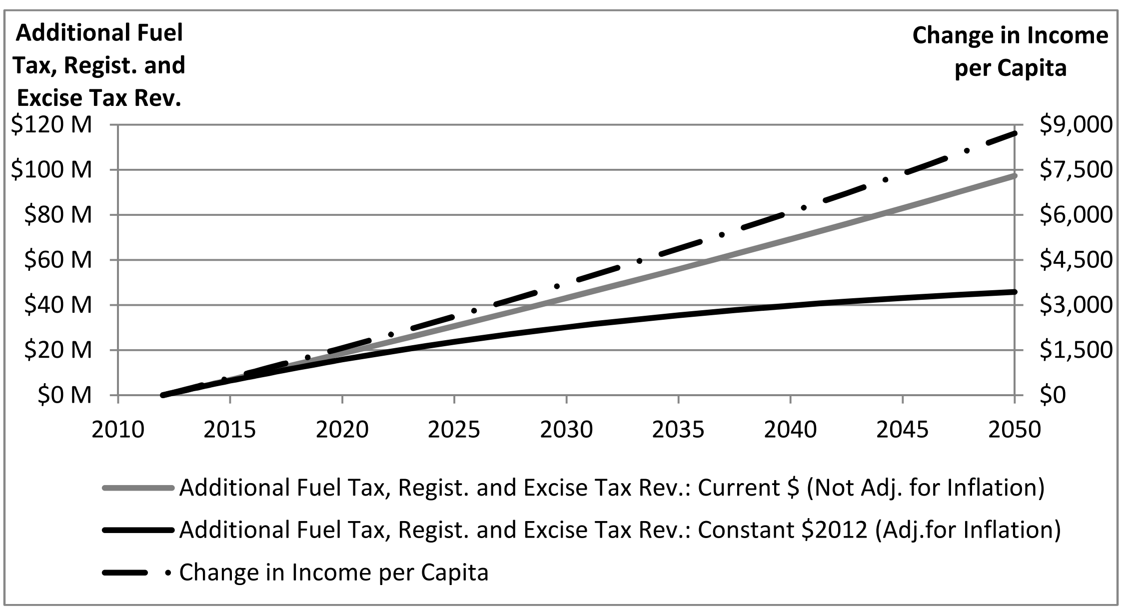


Figure 6.30 Change in State Fuel Tax, Registration, and Excise Tax Revenue Due to Change in per Capita Income

6.3.4.4 Income Summary

Per capita income was found to significantly increase vehicle ownership and VMT. Per capita vehicle ownership is expected to increase from 0.69 to 0.73 due to a 1% annual increase in average income from 2012 to 2050. Overall, the increase in use and ownership is projected to deliver an additional $37.8 million in unadjusted (current) revenue annually by 2050, but due to inflation, the state is projected to lose over $500 million in purchasing power in inflation-adjusted (constant 2012) dollars.

6.3.5 Sensitivity to Manufacturing Employment

A recent rebound in manufacturing jobs, paired with an aggressive tax credit and exemption program, suggests a continued increase in the percentage of manufacturing jobs in Indiana (IEDC, 2015). Analysis in this section investigates the impact of a 1% annual increase in the percentage of manufacturing.

6.3.5.1 Manufacturing and VMT

An increase in the percentage of the labor force employed in manufacturing decreases the expected VMT for both rural and urban census tracts. This may indicate that those employed in this field tend to live closer to their jobs out of convenience or necessity. The inverse relationship between census tract VMT and the fraction of the labor force employed in the manufacturing industry is seen in Figure 6.31. At a rate of a 1% increase per year, the percentage of the state employed in manufacturing would raise from 18.5% in 2012 to 26.2% in 2050, resulting in an estimated reduction of 8.626 billion VMT by 2050 compared to the base case that only considers population shifts.

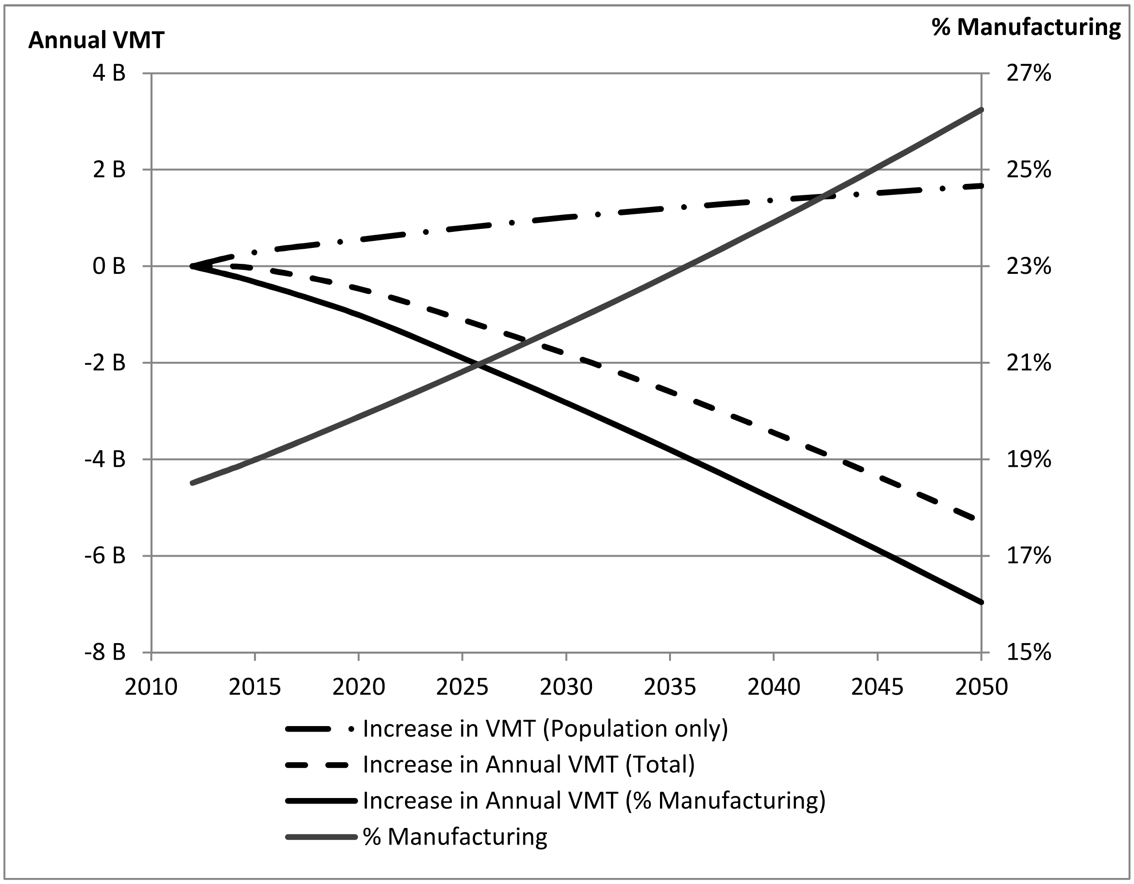


Figure 6.31 Change in VMT Due to Annual Increase in Manufacturing

6.3.5.2 Manufacturing and Vehicle Ownership

The model estimation results in Section 5.4.7 indicate that the effect of an increase in the percentage of manufacturing jobs can be quantified using a lagged independent variable. In other words, an increase in the percentage employed in manufacturing of neighboring census tracts is expected to increase census tract vehicle ownership. At a rate of a 1% increase per year, the percentage employed in manufacturing would raise from 18.5% in 2012 to 26.2% in 2050 (Figure 6.32). This is projected to add 121,000 vehicles, in addition to the projected 590,000 increase in vehicles due to population shifts.

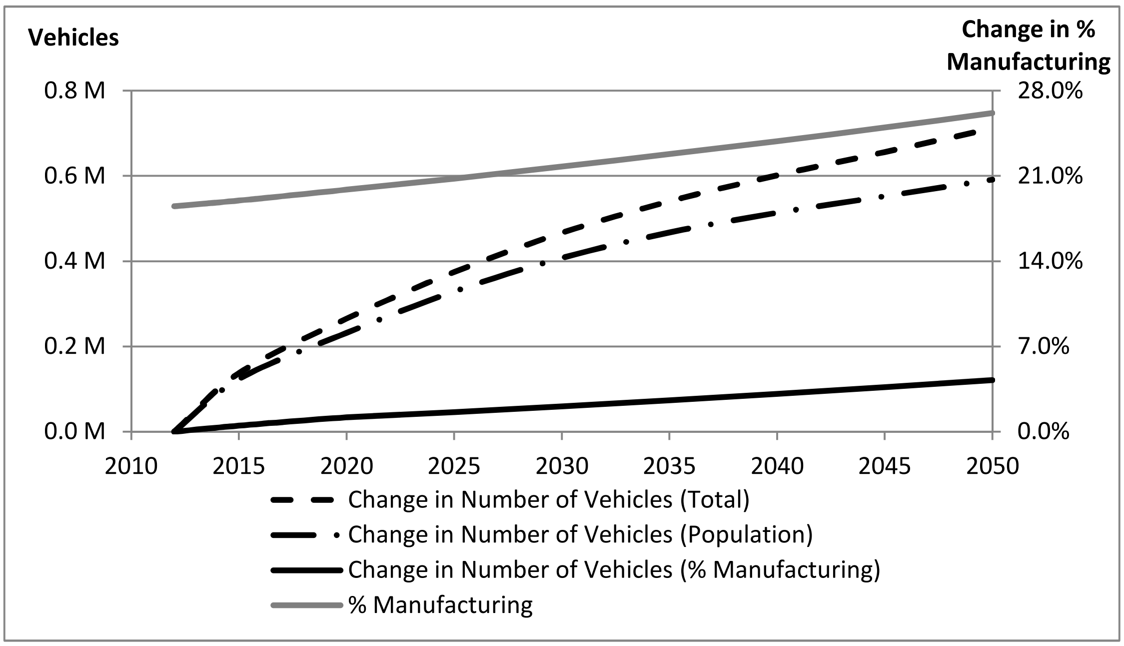


Figure 6.32 Ownership Sensitivity to Annual Increase in Manufacturing

6.3.5.3 Revenue Analysis

The projected reduction in VMT due to increased manufacturing is projected to reduce the inflation-adjusted fuel tax revenue (constant 2012 dollars) by $17.8 million compared to the based case, which only considered an increase in population. This is partially offset by the additional $7.6 million generated from additional registration fees and excise tax (Figure 6.33 and Figure 6.34).

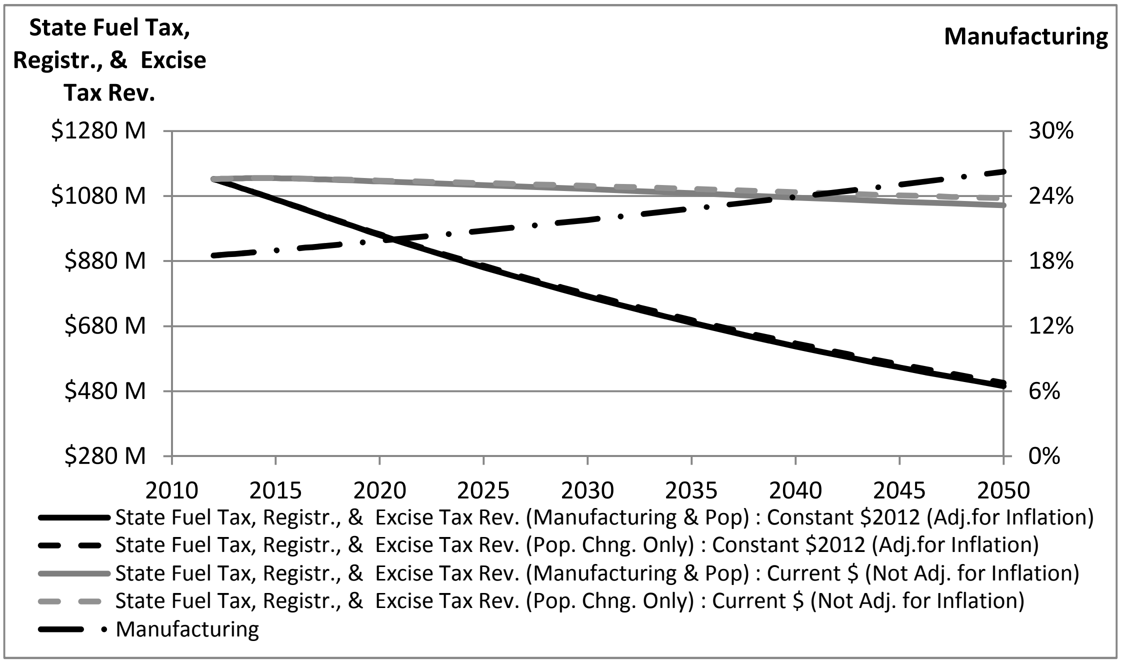


Figure 6.33 State Fuel Tax, Registration, and Excise Tax Revenue from Passenger Vehicles

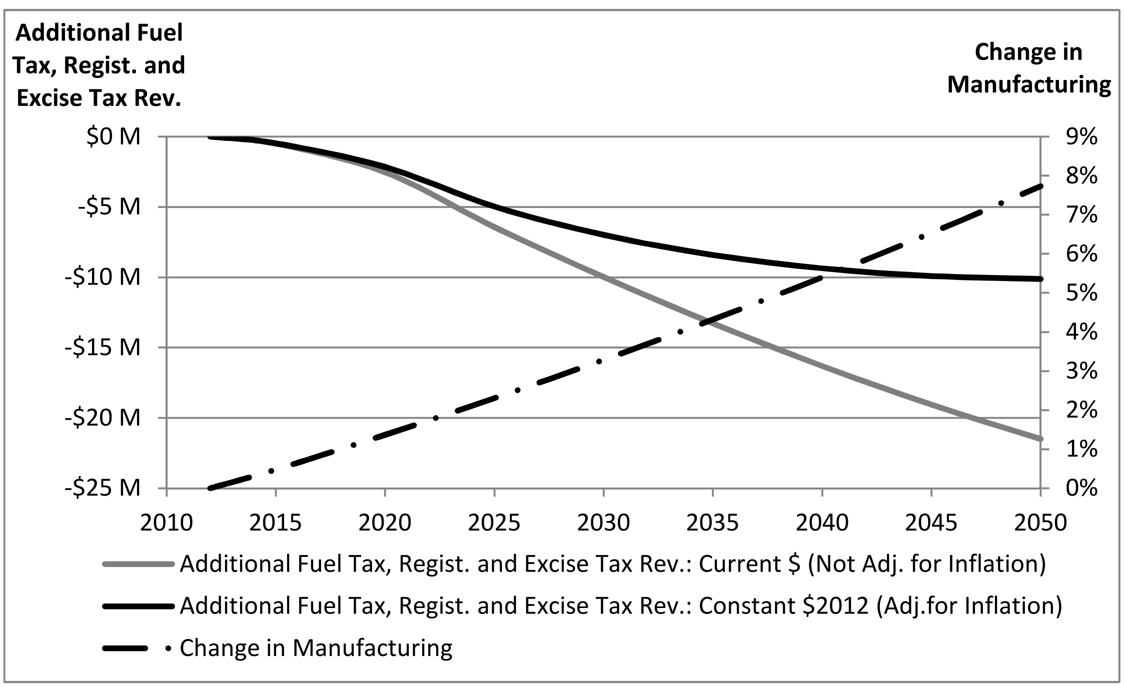


Figure 6.34 Change in State Fuel Tax, Registration, and Excise Tax Revenue Due to Manufacturing

6.3.5.4 Manufacturing Summary

A shift in the percentage of the labor force in the manufacturing industry impacts the expected ownership and use of vehicles. The net impact of decreased fuel tax revenue and increased passenger vehicle registration and excise taxes results in a projected net loss of $10.2 million dollars in inflation-adjusted revenue by 2050.

6.3.6 Sensitivity to Single-Occupancy Commuters

The percentage of single-occupancy commuters in Indiana was 82.4% in 2012 (U.S. Census, 2013). If this rate were to decrease by 0.25% annually, by 2050 the percentage of single-occupancy commuters would reduce to 75.7%. This shift may seem dramatic, but it is reasonable to expect that a prolonged increase in fuel prices or economic recession could have this impact. Furthermore, an increase in population could result in more municipalities offering public transit options and could put pressure on industries to allow their workers to telecommute. The impact in terms of vehicle use and ownership for a sustained decrease in the percentage of single-occupancy commuters (0.25% annually) is investigated in the following sections.

6.3.6.1 Single-Occupancy Commuters and VMT

A decrease in the percentage of single-occupancy commuters is projected to reduce a region's VMT. Commuters shifting to public transit or telecommuting will eliminate VMT due to passenger car commutes. The VMT for individuals who carpool instead of driving alone is equal to 1 divided by the number of commuters per vehicle. A 0.25% annual reduction in the percentage of single-occupancy commuters is projected to reduce VMT by 15.3 billion by 2050, which when combined with the effect of population shifts results in a net reduction of 13.6 billion VMT.

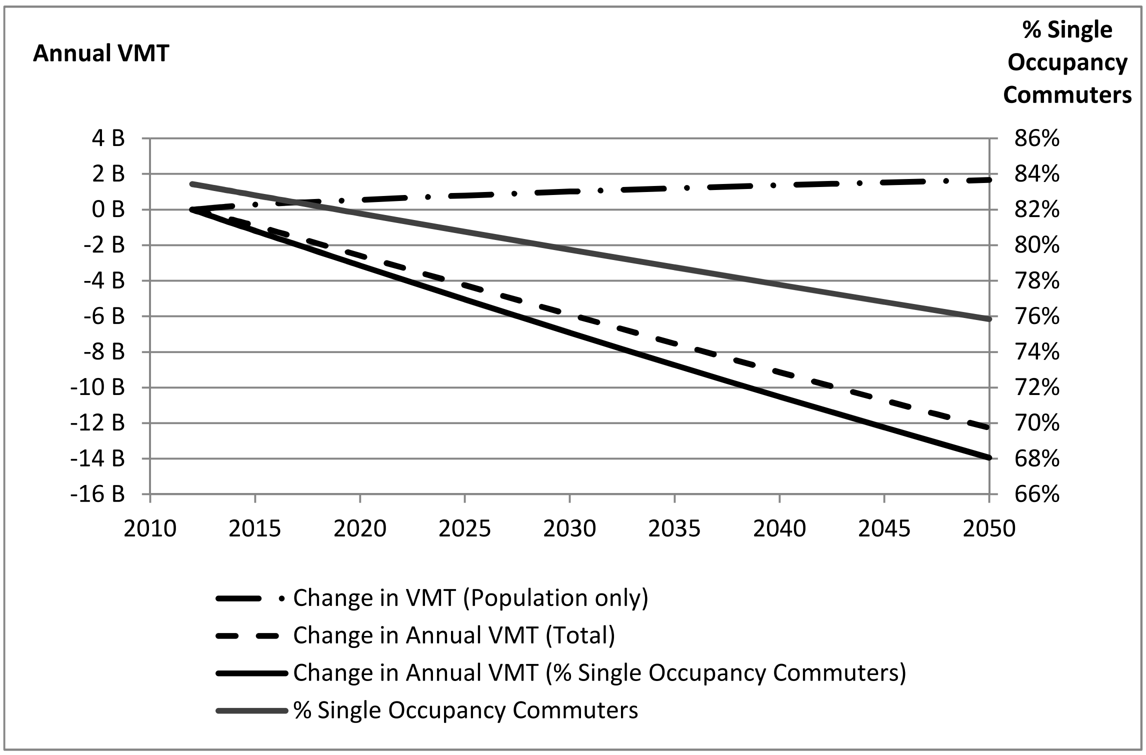


Figure 6.35 Change in VMT Due to an Annual Decrease in the Percentage of Single-Occupancy Commuters

6.3.6.2 Single-Occupancy Commuters and Vehicle Ownership

The number of vehicles in Indiana is expected to be reduced by 290,000 by 2050 due to a 0.25% annually reduction in the percentage of single-occupancy commuters (Figure 6.36). The net effect of a reduction in single-occupancy commuters and an increase in population is an additional 300,000 vehicles in the state.

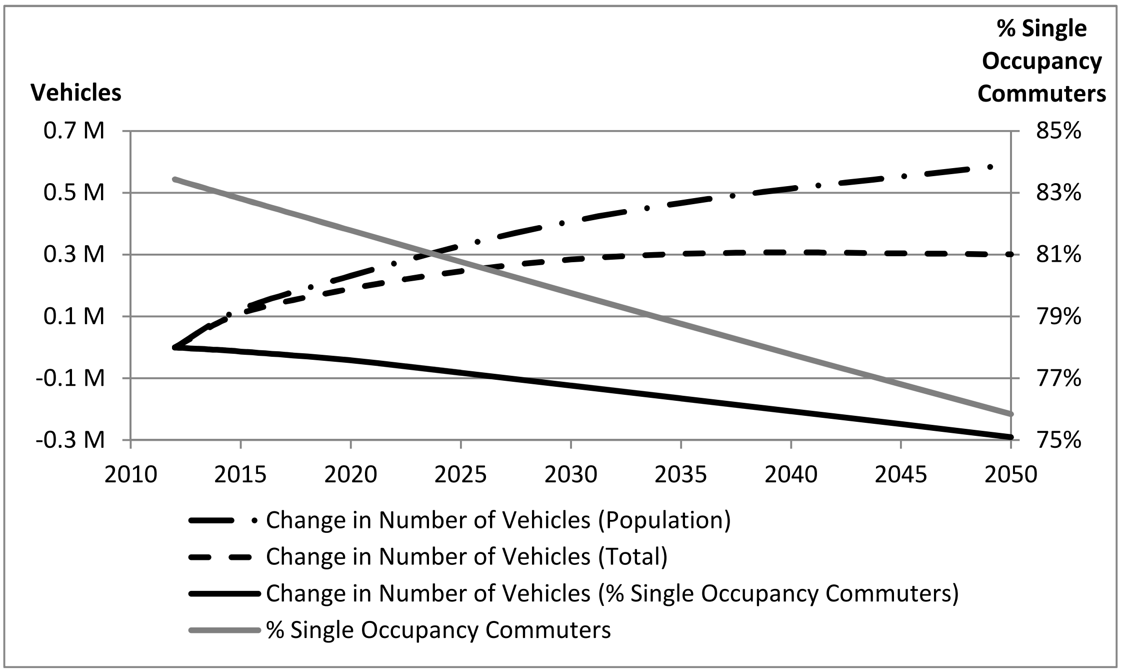


Figure 6.36 Change in Passenger Vehicle Ownership Due to an Annual Decrease in the Percentage of Single-Occupancy Commuters

6.3.6.3 Revenue Analysis

The reduction in VMT and vehicle ownership expected by 2050 in response to a decrease in the percentage of single-occupancy commuters corresponds to an annual loss of $53.2 million dollars compared to the based case, which only considered an increase in population (Figure 6.37 and Figure 6.38).

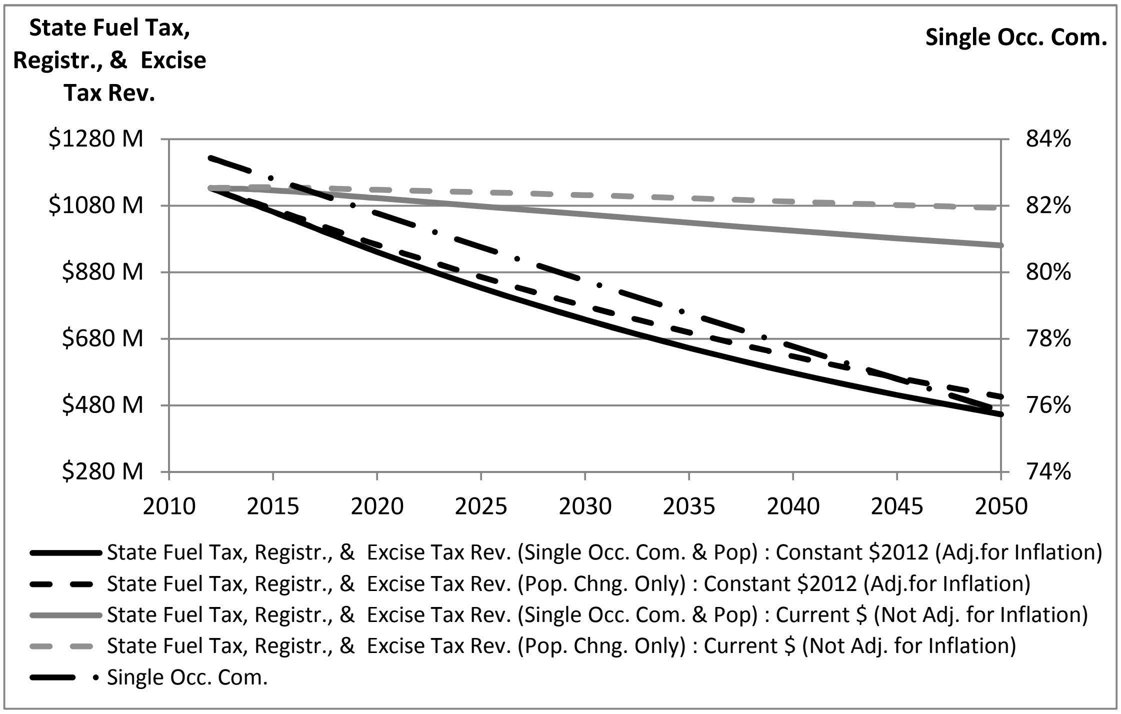


Figure 6.37 State Fuel Tax, Registration, and Excise Tax Revenue from Passenger Vehicles

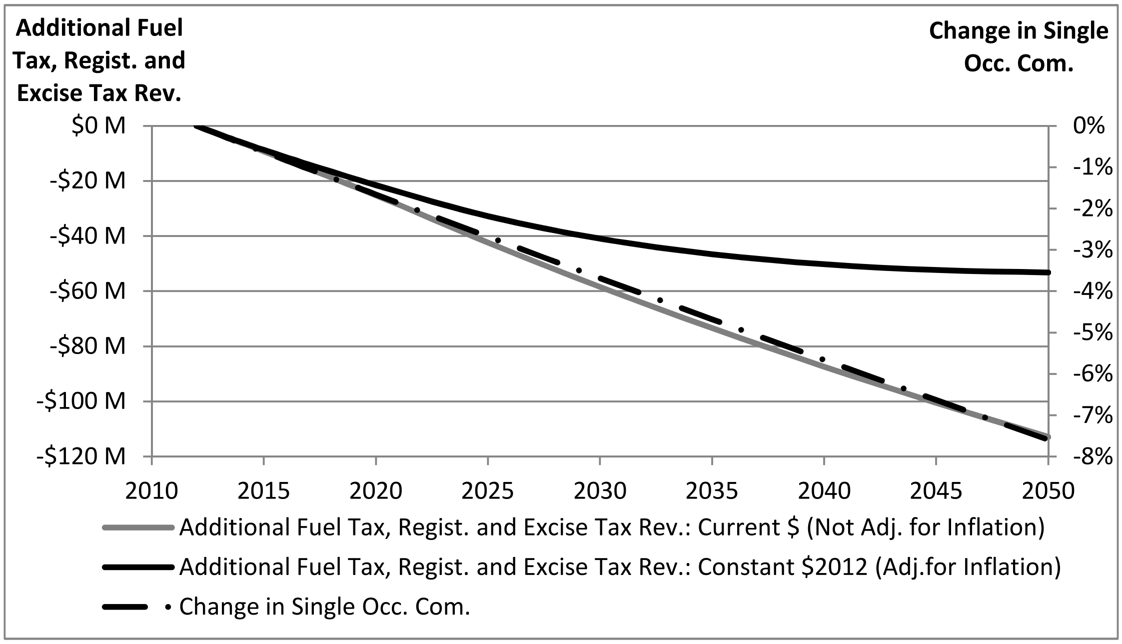


Figure 6.38 Change in State Fuel Tax, Registration, and Excise Tax Revenue Due to Single-Occupancy Commuters

6.3.6.4 Single-Occupancy Commuters Summary

Travel to work is one of the primary reasons why people rely on the highway network. Areas with a lower percentage of single-occupancy commuters experience lower vehicle use and ownership due to a decreased need. Currently, 84% of all commuters in Indiana drive to work in a single-occupancy vehicle (Census, 2014). A consistent decline of 0.25% annually is projected to reduce the state average to 75% by 2050. This would result in 15.6 fewer VMT per year and 290,000 fewer vehicles. These reductions, while potentially beneficial to the environment, would reduce the available funding by $53 million dollars annually by 2050.

6.4 Environmental Impacts

The preceding sections of this chapter focused on the projected impact that long-term shifts in socioeconomic demographics could have on user-generated highway revenue from passenger vehicles. The backbone of this analysis is the spatial econometric models that were used to estimate vehicle use and ownership. The spatial models developed in this dissertation have far-reaching applications in other business processes of highway agencies, including performance predictions, needs assessment, planning, funding allocation, cost allocation, and environmental impact analysis.

Of the business processes, environmental impact analysis is herein singled out for further discussion. Vehicle emissions, such as carbon dioxide, methane, and nitrous oxide, are produced by the combustion of fossil fuels and constitute one of the largest environmental impacts of a highway network.

6.4.1 Carbon Dioxide Equivalent Emissions

The analysis in Section 6.3 can be expanded further to determine the expected change in vehicle emissions due to the projected change in VMT. The total emissions, expressed in terms of carbon dioxide equivalents, can be calculated as follows (EPA, 2013):

$$metric\ tons\ (CO_2E)_i = \sum_{jk} \frac{(VMT_i)(\%_{ijk})}{FE_{ijk}} (ER_K)(\mathrm{EF_{CO_2}})(\mathrm{EF_{CH_4}})(\mathrm{EF_{N_2O}}) \qquad 6\text{-}2$$

where $(CO_2E)_i$ is the equivalent carbon dioxide emission in year i, VMT is the state total VMT in year i, $\%_{ijk}$ is the percentage of the VMT in year i from vehicle class j that for fuel type k (k = gasoline or diesel), FE_{ijk} is the fuel efficiency for year i for vehicle class j for fuel type k, ER_k is the CO_2 emission rate for fuel type k, and EF is the CO_2 equivalency factor for carbon dioxide, methane, and nitrous oxide (1, 1, and 1/0.988 respectively).

The EPA (2005) reported that the average CO_2 emissions from a gallon of gasoline and diesel are 8,788 grams and 10,084 grams, respectively. Figure 6.39 and Figure 6.40 show that total emissions and per capita emissions are projected to reduce over time. This is primarily driven by increased fuel efficiencies, but long-term shifts in manufacturing employment, income, unemployment, and single-occupancy commuters all have the potential to reduce the total VMT, and therefore the total and per capita emission rate.

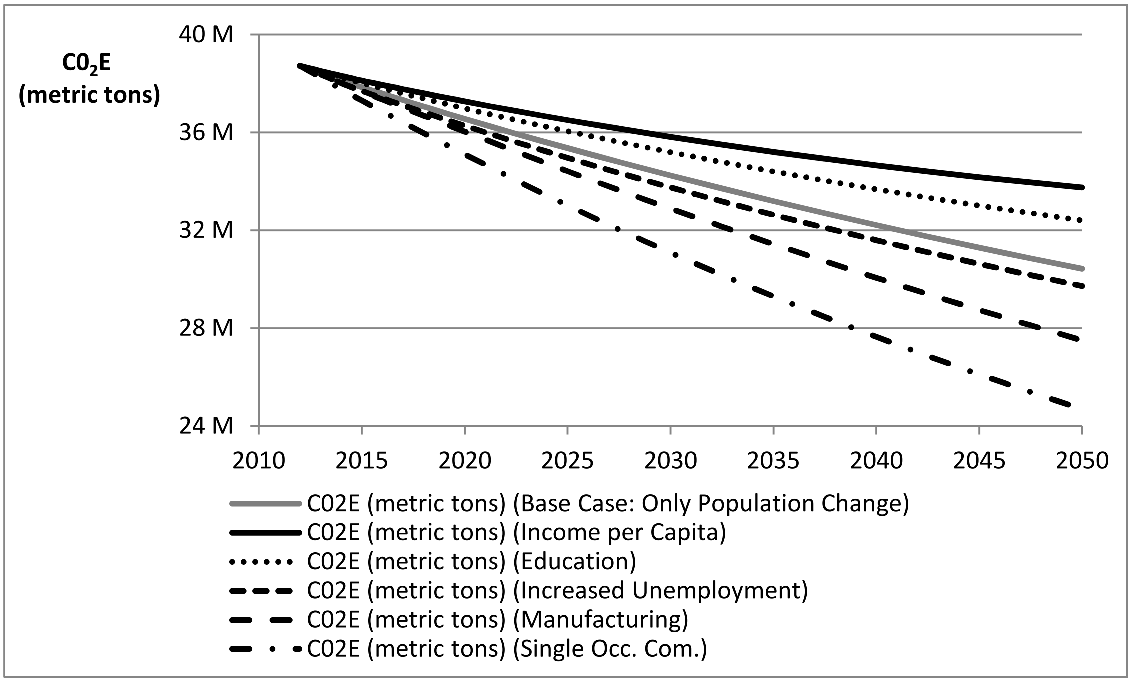


Figure 6.39 Total Emissions (Carbon Dioxide Equivalent)

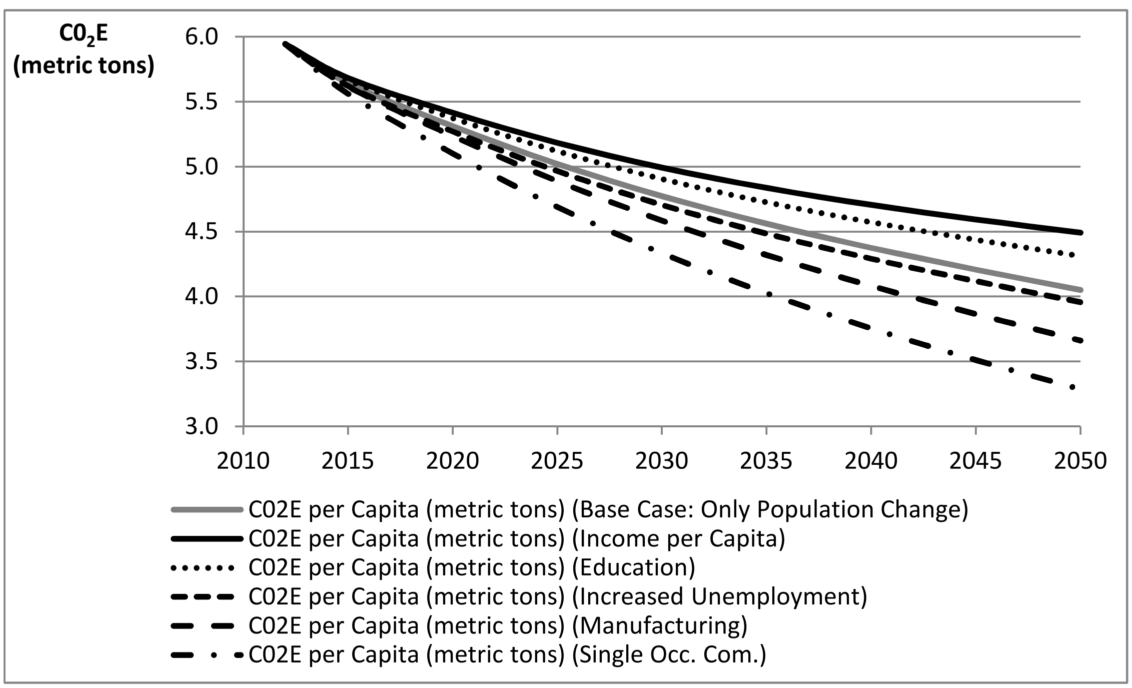


Figure 6.40 Per Capita Emissions (Carbon Dioxide Equivalent)

6.5 Gap Analysis

The sustainability of a highway revenue source is the extent to which it is able to close the funding gap that occurs whenever the needed investment exceeds the available revenue. Chapter 1 introduced definitions for first-order and second-order funding sustainability, which differ based on how investment need is defined. First-order sustainability equates forecasted need to current investment outlays. Second-order sustainability defines forecasted need as the investment needed to ensure all highway infrastructure meets minimum performance thresholds.

An accurate assessment of future funding gaps can allow highway agencies and state and local legislatures to adjust the current tax and fee structure to ensure that the projected investment needs are met or current funding levels are maintained. The latter (first-order sustainability) is discussed in the following sections. These sections detail the adjustments that can be made to the current taxation and fee structure, as well as alternative funding structures, that would ensure that the current level of investment is sustained.

6.5.1 VMT by Out-of-State Vehicles

An important facet of transportation funding sustainability studies is the prospect that new revenue mechanisms or sources will replace existing taxes and fees. One such mechanism, the VMT tax (discussed in detail in Chapter 0), charges users directly for their travel. One major hurdle to VMT-fee implementation at the state level is the inability of the state to collect VMT fees from out-of-state users of the highways. Figure 6.41 illustrates the extent of fuel tax revenue collected from out-of-state passenger vehicles for the socioeconomic scenario presented in Section 6.3 (an annual increase in net population). Between 2012 and 2050, it is expected that Indiana will collect a total of \$1.3 billion (\$50 million annually) in fuel tax revenue from such out-of-state passenger vehicles. Thus, any prospective alternative that will generate revenue from in-state drivers only would need to address the issues of lost revenues (revenues not collected from out-of-state vehicles).

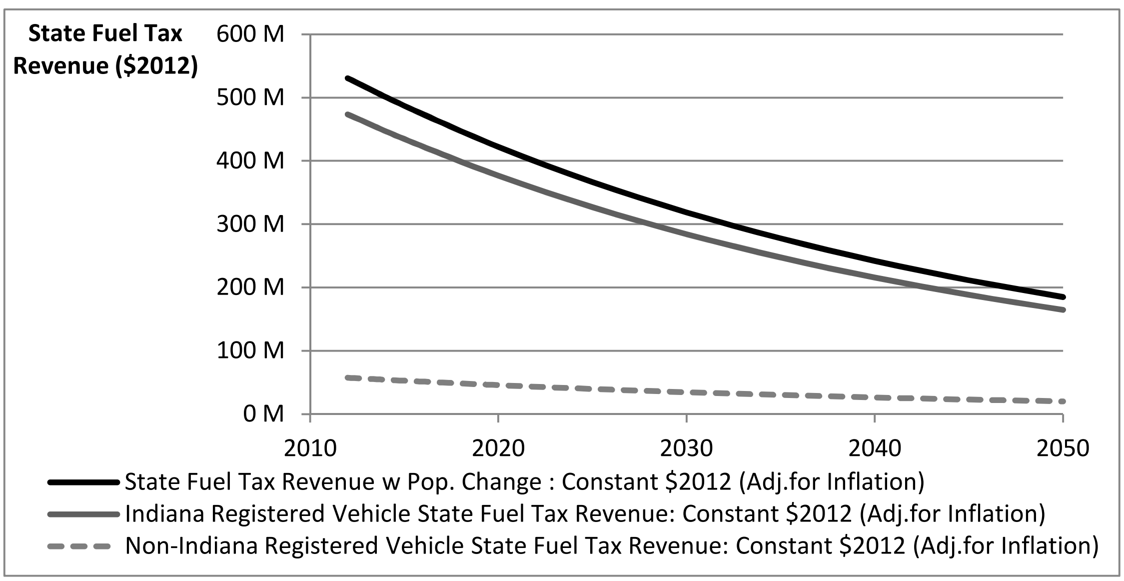


Figure 6.41 Comparison of Fuel Tax Revenue from In-State and Out-of-State Vehicles

6.5.2 Adjusted Fuel Tax

Closing the forecasted funding gap by adjusting the fuel tax rate would ensure that a state is able to capture revenue from in-state and out-of-state users of its infrastructure. The need for first-order sustainability has been defined as inflation-adjusted revenue required to maintain 2012 funding levels. For each of the long-term socioeconomic scenarios discussed Section 6.3 , the gap between the forecasted fuel tax revenue from passenger vehicles (adjusted for inflation) and the 2012 fuel tax revenue was calculated. Then a fuel tax rate that would eliminate the average annual gap was calculated. This process was repeated for the annual gap between the fuel tax, registration, and excise tax revenue. Table 6.1 presents the results of this analysis for the socioeconomic scenario that only considers the change in passenger vehicle use and ownership in response to an increase in net population (all other socioeconomic characteristics were held constant). The results indicate that the gas tax would need to increase by 2.85% annually (equivalent to 0.51¢/gallon in year 1) to ensure the effective revenue generated from fuel tax remains at constant 2012 levels despite expected levels of inflation and increasing fuel economy.

Table 6.1 Adjusted Fuel Tax Rates

Year	Fuel Tax Revenue[A]		Fuel Tax, Registration, and Excise Tax Revenue[B]	
	Gap	Gap with 2.85% Annual Fuel Tax Increase	Gap	Gap with 5.42% Annual Fuel Tax Increase
2012	0.00 M	0.00 M	0.00	0.00 M
2015	-43.44 M	-0.54 M	-62.58 M	-22.42 M
2020	-108.57 M	-2.05 M	-170.23 M	-57.01 M
2025	-164.27 M	-2.51 M	-266.81 M	-69.76 M
2030	-212.10 M	-2.11 M	-354.33 M	-61.16 M
2035	-253.28 M	-0.94 M	-433.77 M	-30.44 M
2040	-288.81 M	0.97 M	-505.48 M	24.19 M
2045	-319.50 M	3.58 M	-569.80 M	104.90 M
2050	-346.04 M	6.97 M	-627.05 M	214.45 M
Average Annual	-204.51 M	0.00 M	-350.53 M	0.00 M

A: passenger vehicle fuel tax revenue for given year minus the 2012 Value (in 2012 dollars)

B: passenger vehicle fuel tax, registration, & excise tax revenue for given year minus the 2012 Value (in 2012 dollars)

If the state wished to close to the gap between forecasted revenue from fuel tax, registration, and excise tax from passenger vehicles and the 2012 funding level, it would require a 5.42% annual fuel tax increase (equivalent to 0.98¢/gallon in year 1). The difference between the 2.85% and 5.42% is the additional funding needed to offset the loss of registration and excise tax revenue due to inflation. This analysis was completed for the projected socioeconomic shifts discussed in Chapter 4 and analyzed in Section 6.3 , and the results are presented in Table 6.2. A sustained increase in per capita income will produce the greatest increase in revenue from passenger vehicles and therefore requires the lowest annual increase in the fuel tax rate (2.58% and 4.98%) to ensure first order sustainability of the fuel tax alone and the fuel tax, registration fees, and excise tax from passenger vehicles, respectively. Conversely, a decrease in single-occupancy commuters would reduce statewide VMT and therefore revenue. In order to ensure first-order sustainability of the fuel tax alone and fuel tax, registration fees, and excise tax from passenger vehicles the fuel tax rate would need to be increased by 3.41% and 6.18%, respectively.

Table 6.2 Annual Increase in Fuel Tax Rate Required to Maintain Equivalent 2012 Funding Levels

	Annual Increase to Close Gap: Fuel Tax Revenue[A]		Annual Increase to Close Gap: Fuel Tax, Registration, and Excise Tax Revenue[B]	
Scenario	Year 1 Increase (¢/gallon)	Annual Increase (%)	Year 1 Rate Increase (¢/gallon)	Annual Increase (%)
Base Case: Population	0.51¢	2.85%	0.98¢	5.48%
1% Annual Increase in Unemployment	0.48¢	2.67%	0.93¢	5.18%
1% Annual Increase in Income	0.47¢	2.58%	0.90¢	4.98%
1% Annual Increase in Employment (% Manufacturing)	0.56¢	3.10%	1.03¢	5.71%
0.25% Annual Decrease in % Single-Occupancy Commuters	0.61¢	3.41%	1.11¢	6.18%
1% Annual Increase in Ed. Attain. (% Bachelor's Degree or Higher)	0.48¢	2.69%	0.94¢	5.21%

A: passenger vehicle fuel tax revenue for given year minus the 2012 Value (in 2012 dollars)

B: passenger vehicle fuel tax, registration, & excise tax revenue for given year minus the 2012 Value (in 2012 dollars)

6.5.3 VMT Fees

The previous section estimated the changes in the fuel tax rate that would be required to eliminate the average annual gap between the projected funding from passenger vehicles and the level of historical funding (2012 levels). Projected increases in vehicle fuel efficiencies are partially responsible for the large revenue gaps. One way to charge users directly in a way that is not susceptible to fluctuations in fuel efficiencies is a fee structure in which motors are charged according to their VMT (please refer to Chapter 2 for a detailed discussion on VMT fees). The VMT fee required to replace the fuel tax revenue from passenger vehicles was calculated, along with the VMT fee required to replace the revenue from registration and excise tax in addition to fuel tax. Additionally, a second set of VMT fees was calculated under the assumption that the state would be unable to collect any revenue from out-of-state vehicles—in other words, the VMT fees consistent with a subsidy of out-of-state vehicles by in-state vehicles.

In 2012, a passenger vehicle VMT fee of 0.84¢/mile would have produced the equivalent revenue as the fuel tax collected from all passenger vehicles (both in-state and out-of-state). To replace the fuel tax, registration, and excise tax revenue from passenger vehicles, this value would need to be increased to 1.78¢/mile. Figure 6.42 provides the projected VMT fee rates (in unadjusted dollars) that would ensure that the average annual effective revenue (revenue adjusted for inflation) remains at 2012 funding levels. By 2050, these rates can vary by as much as 1.18¢/mile depending on future socioeconomic conditions.

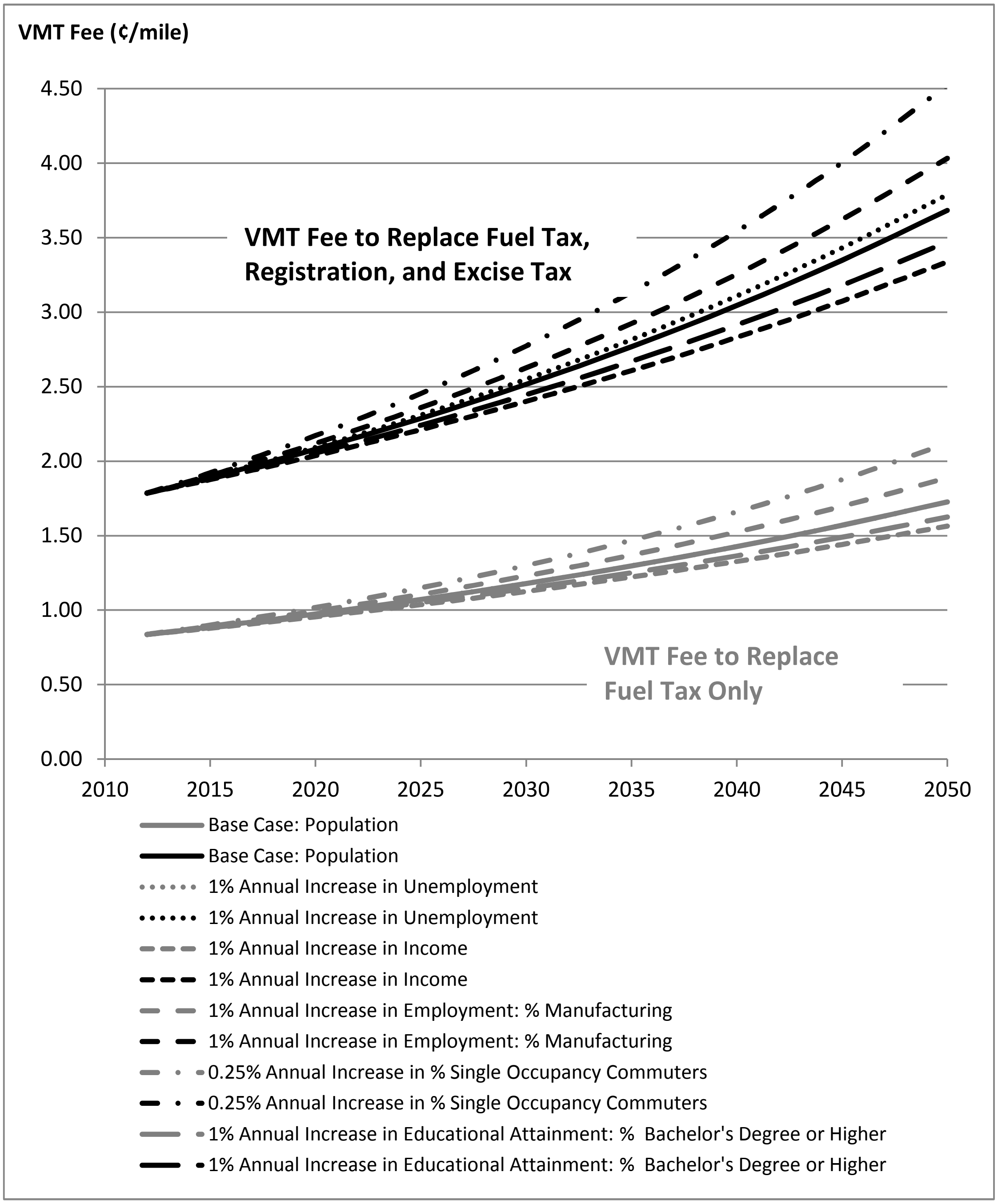


Figure 6.42 Required Passenger Vehicle VMT Fee to Maintain Equivalent 2012 Funding Levels

Table 6.3 shows that, in order to maintain 2012 fuel tax funding levels, the passenger vehicle VMT fee would need to increase by 1.66% to 2.47% annually depending on the socioeconomic scenario. In the first year this is equivalent to a 0.014 to 0.021 ¢/VMT increase in the VMT fee for first-order sustainability of current fuel tax revenue. These values increase to 1.66 to 2.47 ¢/VMT in the first year to ensure first-order sustainability of the current fuel tax, registration, and excise tax revenue from personal vehicles.

Table 6.3 Annual Increase in VMT Tax Rate Required to Maintain Equivalent 2012 Funding Levels

	Annual Increase to Close Gap: Fuel Tax Revenue[A]		Annual Increase to Close Gap: Fuel Tax, Registration, and Excise Tax Revenue[B]	
Scenario	Year 1 Increase (¢/VMT)	Annual Increase (%)	Year 1 Increase (¢/VMT)	Annual Increase (%)
Base Case: Population	0.016¢	1.92	0.034¢	1.92
1% Annual Increase in Unemployment	0.016¢	2.00	0.036¢	2.00
1% Annual Increase in Income	0.014¢	1.66	0.030¢	1.66
1% Annual Increase in Employment (% Manufacturing)	0.018¢	2.17	0.039¢	2.17
0.25% Annual Decrease in % Single-Occupancy Commuters	0.021¢	2.47	0.044¢	2.47
1% Annual Increase in Ed. Attain. (% Bachelor's Degree or Higher)	0.015¢	1.76	0.032¢	1.76

A: passenger vehicle fuel tax revenue for given year minus the 2012 Value (in 2012 dollars)

B: passenger vehicle fuel tax, registration, & excise tax revenue for given year minus the 2012 Value (in 2012 dollars)

This analysis assumes the state would be able to collect VMT fees from all passenger vehicles that use the state's highway system. However, without a unified national system, it is conceivable that the state would be unable to collect VMT fees from vehicles registered outside of their jurisdiction. Therefore, the previous analysis was recalculated assuming VMT could be collected from only 88.8% of the network usage (Section 3.4 detailed the methodology that was used to determine the extent of system usage by out-of-state users). Over time, shifts in population due to migration have the potential to change the share of usage by out-of-state vehicles. However, these impacts were found to be negligible on the order of 0.001% to 0.005% change per year (1/1000th of 1% to 1/200th of 1%). Therefore, in this dissertation the share of usage by out-of-state vehicles was assumed to be stable over time within the case study period.

The analysis showed that, in 2012, a passenger vehicle VMT fee of 0.94¢/mile for in-state vehicles would have produced the equivalent revenue as the fuel tax collected from all passenger vehicles (both in-state and out-of-state) in that year. This value would need to be increased to 2.01¢/mile to replace the fuel tax, registration, and excise tax revenue from passenger vehicles for that year. The annual increase in VMT fee required to maintain 2012 funding levels is presented in Table 6.4. The passenger vehicle VMT fee collected from Indiana residents would need to increase by 1.66% to 2.47% annually, depending on the socioeconomic scenario.

Table 6.4 Annual Increase in VMT Tax Rate Required to Maintain Equivalent 2012 Funding Levels (State Residents Only)

Scenario	Annual Increase to Close Gap: Fuel Tax Revenue[A]		Annual Increase to Close Gap: Fuel Tax, Registration, and Excise Tax Revenue[B]	
	Year 1 Increase (¢/VMT)	Annual Increase (%)	Year 1 Increase (¢/VMT)	Annual Increase (%)
Base Case: Population	$0.018	1.92	$0.039	1.92
1% Annual Increase in Unemployment	$0.018	2.00	$0.040	2.00
1% Annual Increase in Income	$0.016	1.66	$0.033	1.66
1% Annual Increase in Employment (% Manufacturing)	$0.020	2.17	$0.044	2.17
0.25% Annual Decrease in % Single-Occupancy Commuters	$0.023	2.47	$0.050	2.47
1% Annual Increase in Ed. Attain. (% Bachelor's Degree or Higher)	$0.017	1.76	$0.035	1.76

A: passenger vehicle fuel tax revenue for given year minus the 2012 Value (in 2012 dollars)
B: passenger vehicle fuel tax, registration, & excise tax revenue for given year minus the 2012 Value (in 2012 dollars)

6.5.4 Rate Sensitivity to Change in Need

Sections 6.5.2 and 6.5.3 investigated the changes that would ensure first-order sustainability of the current fuel tax and proposed VMT fees under the predefined forecast socioeconomic conditions. In this analysis, the need was held at a constant value that is equivalent to the inflation-adjusted revenue generated in 2012. However, need can increase or decrease in future years for a variety of reasons. For example, an increase in material costs or the effect of deferred maintenance and rehabilitation may require funding levels to be increased. Conversely, if material costs reduce or improvements in construction materials, practices, and delivery reduce project lifecycle costs then needed funding would reduce. To investigate these potential changes in forecast need, the sensitivity of the annual increase in the fuel tax and VMT fee to changes in the forecast need are presented in Table 6.5 and Table 6.6, respectively. Table 6.5 shows that even if the needed revenue decreased 2% per year, the fuel tax would not provide first-order sustainability under any of the forecast socioeconomic scenarios without an annual increase in the fuel tax rate. However, Table 6.6 shows that a VMT fee could be sustainable under several scenarios without an annual increase in the VMT fee if the needed revenue decreased 2% per year.

Table 6.5 Forecast Need Sensitivity Analysis: Annual Increase in Fuel Tax Rate Required to Maintain Equivalent 2012 Funding Levels

	Annual Change in Need				
	-2%	-1%	0%	+1%	+2%
Scenario	Annual Increase in Fuel Tax Rate to Close Fuel Tax Revenue Gap				
Base Case: Population	0.80%	1.83%	2.85%	3.88%	4.91%
1% Annual Increase in Unemployment	0.63%	1.65%	2.68%	3.70%	4.72%
1% Annual Increase in Income	0.54%	1.56%	2.59%	3.61%	4.63%
1% Annual Increase in Employment (% Manufacturing)	1.04%	2.07%	3.10%	4.13%	5.16%
0.25% Annual Decrease in Percentage Single-Occupancy Commuters	1.34%	2.38%	3.41%	4.44%	5.48%
1% Annual Increase in Ed. Attain. (% Bachelor's Degree or Higher)	0.64%	1.67%	2.69%	3.72%	4.74%

Table 6.6 Forecast Need Sensitivity Analysis: Annual Increase in VMT Fee Required to Maintain Equivalent 2012 Funding Levels

Scenario	Annual Change in Need				
	-2%	-1%	0%	+1%	2%
	Annual Increase in VMT Fee to Close Fuel Tax Revenue Gap				
Base Case: Population	-0.12%	0.91%	1.93%	2.95%	3.97%
1% Annual Increase in Unemployment	-0.04%	0.98%	2.00%	3.02%	4.04%
1% Annual Increase in Income	-0.37%	0.64%	1.66%	2.68%	3.70%
1% Annual Increase in Employment (% Manufacturing)	0.12%	1.14%	2.17%	3.19%	4.22%
0.25% Annual Decrease in % Single-Occupancy Commuters	0.42%	1.45%	2.48%	3.50%	4.53%
1% Annual Increase in Ed. Attain. (% Bachelor's Degree or Higher)	-0.27%	0.75%	1.77%	2.78%	3.80%

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CHAPTER 7. SUMMARY AND CONCLUSIONS

7.1 Overview

Across the United States, transportation agencies continue to grapple with diminishing highway revenues due to the combined effects of increased fuel economies and inflation. When the revenue generation is consistently below the required or historical levels, the funding gap leads to further growth of the cumulative deficit. The effective revenue generated from passenger vehicle use and ownership is projected to continue to decline unless adjustments are made to make these funding sources more sustainable. Past research on highway funding sustainability used simple projections of historical data on highway funding or vehicle use. However, these past studies have identified that shifts in social demographics and economic characteristics are expected to be the root cause of shifting travel demand and vehicle use, and consequently highway revenue.

7.2 Contributions of this Dissertation

This dissertation developed a unified framework in which the socioeconomic characteristics of a census tract and its neighboring regions are used to make projections of future vehicle use and ownership, and consequently future highway revenue. This dissertation has made three unique contributions to the field of highway finance. First, it presented a unified overarching framework by which socioeconomic data can be used to project future highway revenue from different vehicle classes. Second, it developed an enhanced methodology for VMT estimation within a geographic region on the basis of traffic volume counts and spatial interpolation. Third, this dissertation applied spatial econometrics to estimate the levels of vehicle use and ownership by accounting for the spatial dependence and heterogeneity that are typically inherent in socioeconomic and vehicle use and ownership data. These three contributions provide new insights that can be used across transportation disciplines.

The dissertation used the revenue projections to (i) calculate the required extent of adjustments to the current gas tax that would ensure that the effective level of revenue would be sustained; and (ii) investigate the sustainability of VMT fees as an alternative revenue source.

7.3 Current System Usage

For analyzing the factors that influence the extent of travel, reliable assessments of road usage are needed. The variability in vehicle travel data was addressed using Ordinary Kriging estimation, a geostatistical spatial estimation methodology that uses the distance and auto-correlation between data collection sites to impute unknown values into a random field. Ordinary Kriging estimation was also implemented to provide reliable estimates of the percentage of out-of-state vehicles at the network and census tract levels. Kriging estimation duly accounts for the clustering of data collection sites, which characterizes the locations of long-term traffic counts. The VMT for all roads was determined using a combination of location-specific traffic count data, spatial interpolation, gasoline and diesel fuel sales, and fleet fuel efficiencies.

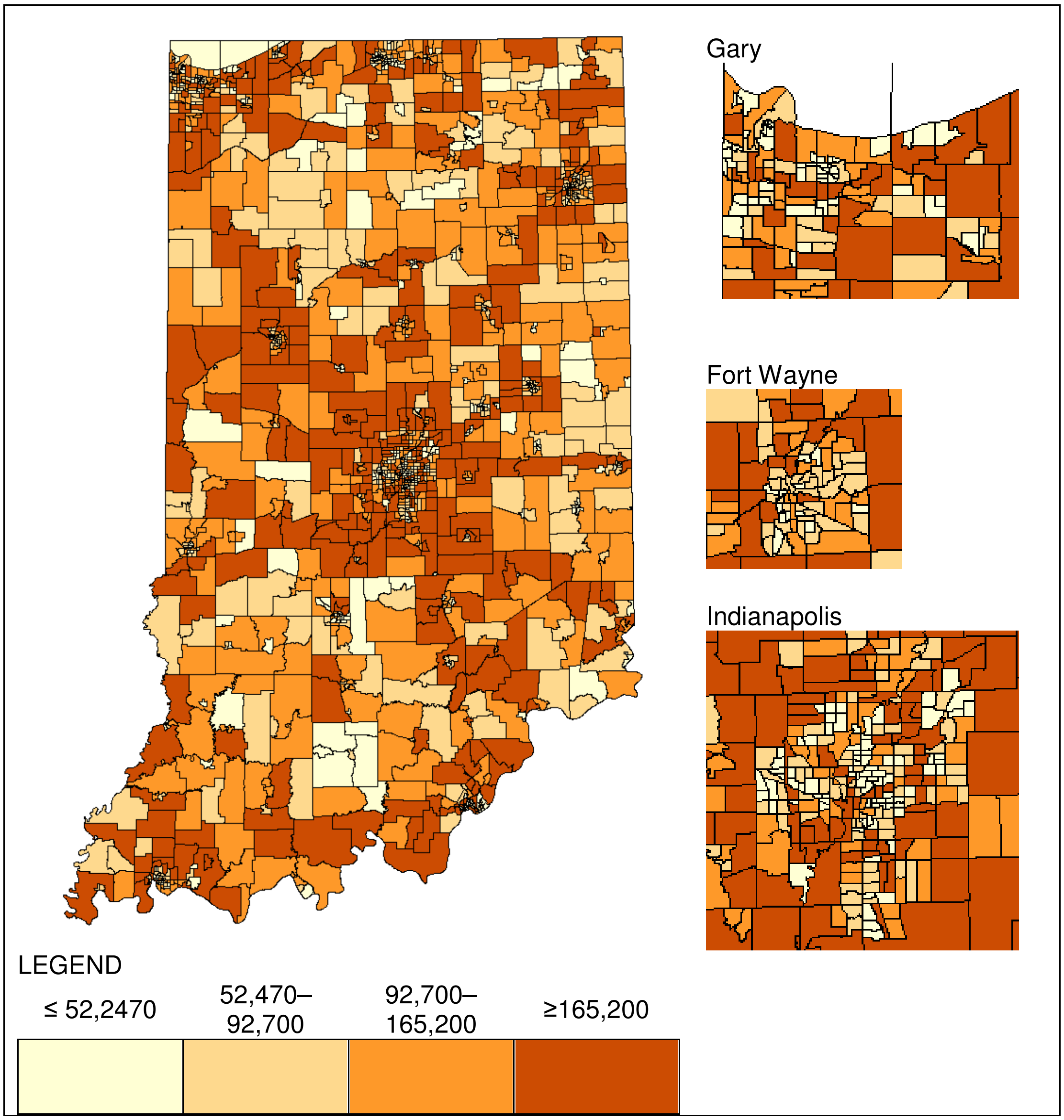

Figure 7.1 Census Tract Daily VMT Map

The extent of fuel sales and VMT attributed to out-of-state highway users was determined through extensive field data collection and analysis of fuel purchases. This data was subsequently used to evaluate the sustainability of alternative funding mechanisms. Spatial analysis using Kriging estimation provided roadway-specific splits of in-state and out-of-state VMT that were then averaged for each census tract. Average results for Indiana are presented in Figure 7.2. The results show that, in Indiana, 11.12% of the passenger vehicle VMT and 10.83% of fuel sales can be attributed to out-of-state vehicles.

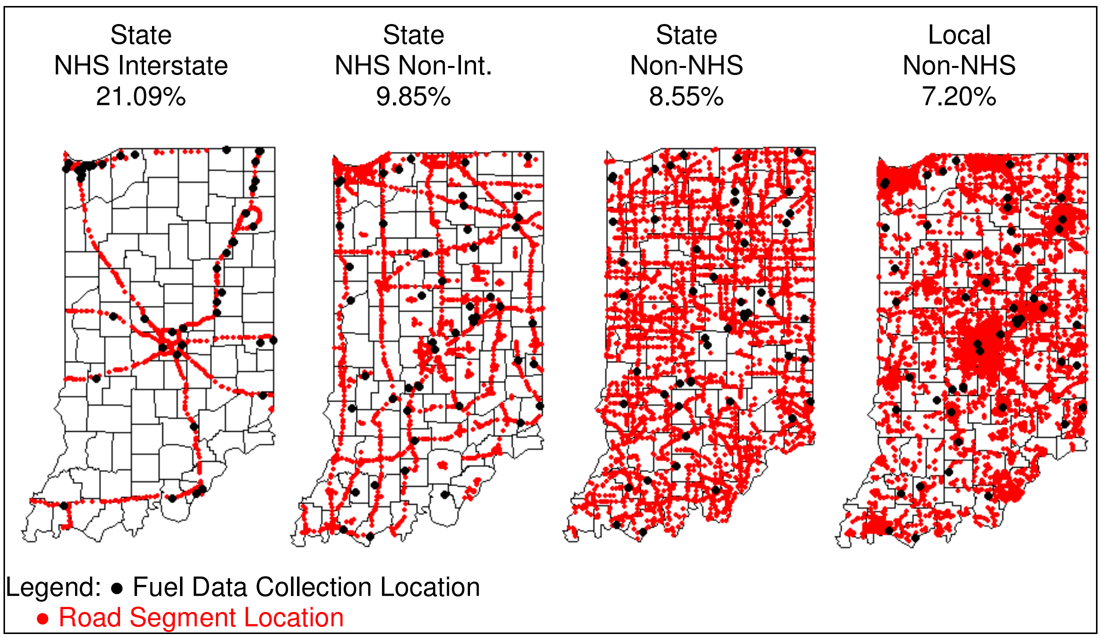

Figure 7.2 Fraction of Personal Vehicle VMT by Out-of-State Users of Indiana's Highways

7.4 Social and Economic Factors

Previous highway funding studies have identified that shifts in socioeconomic demographics are expected to influence future vehicle use and ownership. Despite the abundance of socioeconomic data made available by the United States Census Bureau, the number of studies that have attempted to draw empirical relationships between socioeconomic characteristics and revenue generation is severely limited. Lack of research on this topic has been attributed to a lack of corresponding vehicle use data and failure to apply spatial modeling techniques. In this dissertation, the former issue was addressed in the VMT methodology presented in Chapter 3, and the latter issue was addressed through the development of spatial econometric models in Chapter 5.

This dissertation identified a number of long-term socioeconomic factors that are expected to influence the state's capability generate revenue from passenger vehicles in the long term: population, education, unemployment, income, the manufacturing industry, and commuting trends. The magnitude and direction of the influence of each factor was also quantified. Compelling evidence, including the sustained historical population growth rate and legislative mandates concerning higher education and tax breaks for manufacturing, suggest that short-term and long-term changes in these characteristics are not only likely but will also influence highway revenue in the long-term.

7.5 Spatial Econometric Analysis

The non-constancy of vehicle use and ownership over space, if unaccounted for, can lead to biased, inefficient, and inconsistent results in any model that predicts/estimates these attributes. To account for this issue, this dissertation investigated the use of several different spatial econometric functional forms to explain the relationship between socioeconomic factors and census tract vehicle use and ownership. Individuals not only drive in their census tract, but also are likely to drive in neighboring census tracts (at a rate that progressively decays for tracts of increasing distance from their home tracts). Additionally, people are generally less likely to own a vehicle if they live in a census tract or near one that affords them services that do not require the use of a personal vehicle. These impacts can be identified and quantified using lagged socioeconomic independent variables (cross-regressive terms) for local spillovers. There may also be direct spatial spillovers in the sense that some people may avoid areas with greater levels of traffic. This dissertation included a lagged dependent variable to account for global spillovers.

The Spatial Durbin model was used to estimate vehicle use. The model accounts for local and global spillovers by estimating lagged independent and dependent variables, respectively. The inclusion of spatial regimes and lagged variables removed the effect of spatial error. Spatial regimes were also significant in the spatial vehicle-ownership model. However, even after the inclusion of spatial regimes, lagged independent, and lagged dependent variables, the data still exhibited statistically significant spatial error. To account for the spatial dependence and error, the dissertation estimated a General Spatial Durbin model.

7.6 Revenue Sustainability

This dissertation used the forecast shifts in socioeconomic demographics as inputs in the developed vehicle-use and vehicle-ownership spatial models to estimate the future transportation revenue that can be expected from passenger vehicle fuel tax, registration fees, and excise tax. This dissertation also determined that the projected increases in fuel economies and inflation will lead to a situation where all of the current revenue sources are unsustainable, regardless of the change in socioeconomic demographics. This dissertation then calculated the needed level of adjustments to the current tax and fee structure to ensure first-order sustainability. The current fuel tax rate would need to be increased by 2.58% to 3.41% every year (depending on the socioeconomic shifts) to recoup the effective fuel tax losses projected in the forthcoming decades. These values would need to be increased to 4.98% to 6.18% to cover the losses from fuel tax, registration, and excise tax.

Projected increases in vehicle fuel efficiencies are partially responsible for the reduction in gas consumption, and therefore in gas tax revenue. One mechanism of direct user charging that is not susceptible to increases in fuel efficiencies is a fee structure in which vehicles are charged according to their VMT. Figure 7.3

provides an estimate of passenger vehicle VMT fees that would ensure sustainable revenue generation equal to the revenue generated from fuel tax, registration fees, and excise tax in 2012 (adjusted for inflation).

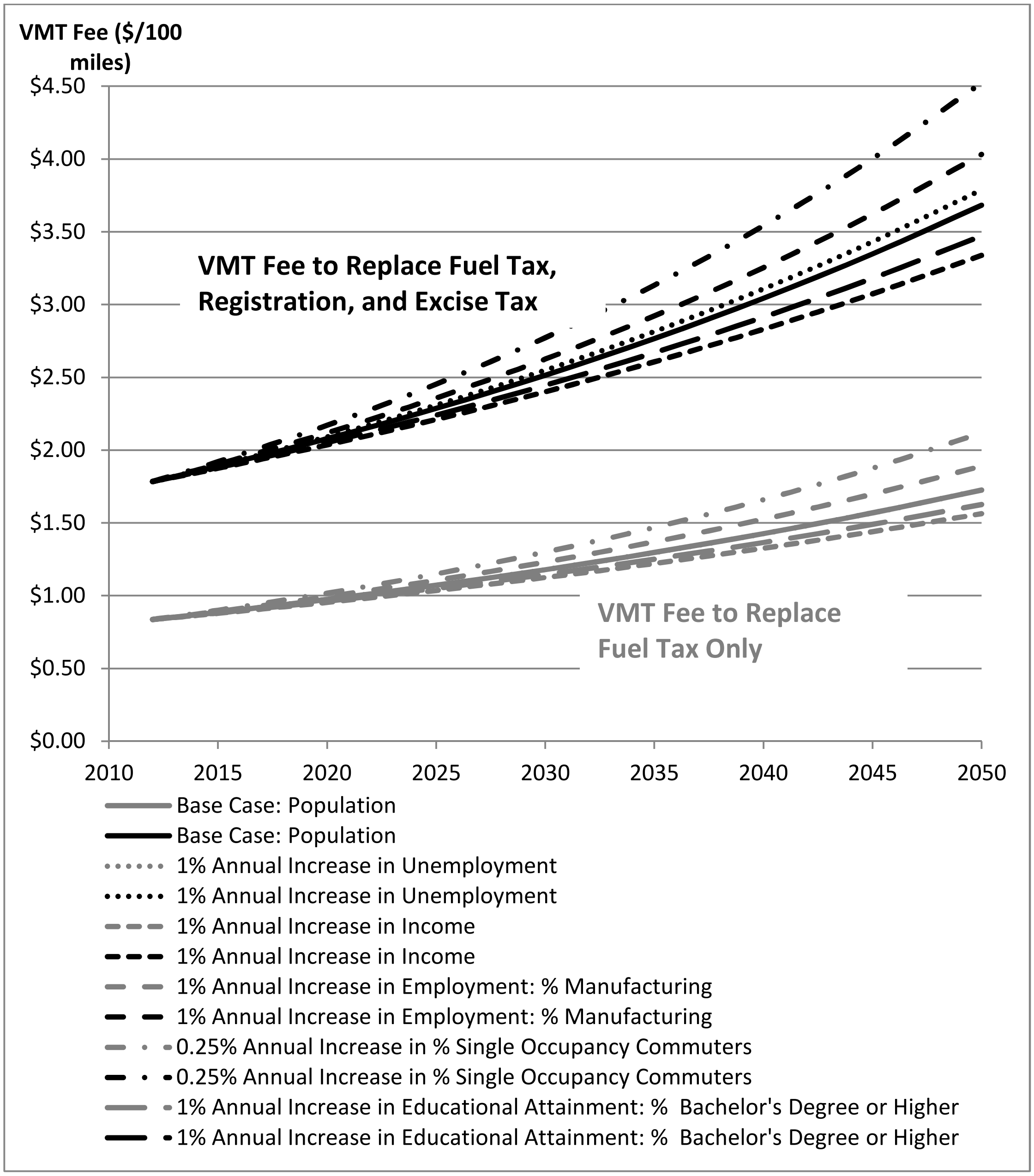

Figure 7.3 Sustainable Vehicle Personal Vehicle VMT Fees

7.7 Conclusions

The current transportation funding structure has remained largely unchanged for decades. Stagnant funding, increasing vehicle fuel efficiencies, and inflation have decreased the effective level of revenue generation. The ability of a state to achieve sustained levels of user revenue over the long-term depends on these factors along with shifting socioeconomic demographics. This dissertation has provided a unified framework to help highway agencies forecast future revenue as a function of the socioeconomic characteristics of their state. Ultimately, this research product can be used to identify changes to the current taxation and fee structure that will eliminate the funding gap and provide sustainable highway infrastructure funding.

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APPENDICES

Appendix A. Descriptive Statistics of Socioeconomic Data (U.S. Census, 2014)

	Mean	St. Dev.	Median	Min	1st Quartile	3rd Quartile	Max	Inter Quartile Range
% VMT on State	0.43	0.32	0.44	0.00	0.11	0.70	1.00	0.59
% VMT on Local	0.57	0.32	0.56	0.00	0.30	0.89	1.00	0.59
% VMT on Interstate	0.11	0.23	0.00	0.00	0.00	0.00	0.97	0.00
% VMT on NHS non-Int	0.19	0.23	0.10	0.00	0.00	0.34	1.00	0.34
% VMT on non-NHS	0.12	0.22	0.00	0.00	0.00	0.18	1.00	0.18
Daily VMT on State	70032	95268	38973	0	5397	91483	674039	86085
Daily VMT on Local	58247	47822	46976	0	26438	76692	416690	50254
Daily VMT on Interstate	28658	75446	0	0	0	0	600558	0
Daily VMT on NHS non-Int	26558	44699	9358	0	0	37793	541295	37793
Daily VMT on non-NHS	14817	25525	0	0	0	21824	174551	21824
% CLM on State	0.12	0.17	0.08	0.00	0.02	0.16	1.00	0.14
% CLM on Local	0.88	0.17	0.92	0.00	0.84	0.98	1.00	0.14
% CLM on Interstate	0.02	0.06	0.00	0.00	0.00	0.00	0.81	0.00
% CLM on NHS non-Interstate	0.04	0.08	0.02	0.00	0.00	0.06	1.00	0.06
% CLM on non-NHS	0.06	0.13	0.00	0.00	0.00	0.07	1.00	0.07
CLM on State	7.74	11.02	2.85	0.00	0.49	10.87	73.41	10.38
CLM on Local	54.85	60.58	30.87	0.00	14.81	73.95	476.34	59.13
CLM on Interstate	0.97	2.65	0.00	0.00	0.00	0.00	28.79	0.00
CLM on NHS non-Interstate	2.23	3.62	0.68	0.00	0.00	2.89	29.77	2.89
CLM on non-NHS	4.54	8.58	0.00	0.00	0.00	5.31	54.13	5.31
$ per VMT Auto	0.02	0.01	0.02	0.00	0.02	0.03	0.05	0.01
$ per VMT Truck	0.18	0.06	0.18	0.00	0.13	0.23	0.25	0.10
$ per VMT	0.04	0.01	0.03	0.00	0.03	0.04	0.08	0.01
$ per Day	4753	4526	3375	0	1716	6211	32513	4496
% Auto on State	0.70	0.35	0.86	0.00	0.71	0.92	0.99	0.21
% Auto on Local Network	0.93	0.11	0.95	0.00	0.93	0.95	0.95	0.02

	Mean	St. Dev.	Median	Min	1st Quartile	3rd Quartile	Max	Inter Quartile Range
% Auto on All	0.90	0.07	0.93	0.59	0.88	0.95	0.98	0.06
% M. Cycle on State	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00
% Cars on State	0.51	0.25	0.63	0.00	0.57	0.66	0.72	0.09
% SUV on State	0.20	0.10	0.25	0.00	0.22	0.26	0.29	0.04
% Class 9 Trucks on State	0.05	0.04	0.04	0.00	0.02	0.08	0.29	0.06
% Class 9 Trucks in truck traffic stream on the state	0.44	0.24	0.51	0.00	0.35	0.60	0.80	0.25
Local VMT	58285	47814	46996	0	26450	76703	416690	50253
% Motorcycles on Local Network	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.00
% Cars on Local Network	0.65	0.08	0.66	0.00	0.65	0.66	0.67	0.01
% SUV on Local Network	0.28	0.03	0.28	0.00	0.28	0.29	0.29	0.01
% Class 9 Trucks on State Network	0.03	0.01	0.03	0.00	0.03	0.04	0.07	0.01
% Class 9 Trucks in truck traffic stream on the Local network	0.56	0.08	0.59	0.00	0.58	0.59	0.64	0.00
Estimate; EMPLOYMENT STATUS—Population 16 years and over	3360	1523	3134	0	2328	4145	12373	1817
Estimate; EMPLOYMENT STATUS—In labor force	2184	1089	1995	0	1451	2735	9746	1284
Estimate; EMPLOYMENT STATUS—In labor force—Civilian labor force—Unemployed	205	111	188	0	125	261	850	136
Estimate; EMPLOYMENT STATUS—Not in labor force	1177	580	1086	0	787	1437	5550	650
Percent; EMPLOYMENT STATUS—Percentage Unemployed	10.68	6.32	9.20	0.00	6.40	13.30	44.80	6.90
Estimate; COMMUTING TO WORK—Car, truck, or van—drove alone	1606	907	1454	0	999	2047	7820	1048
Estimate; COMMUTING TO WORK—Car, truck, or van—carpooled	180	119	155	0	99	230	1265	131
Estimate; COMMUTING TO WORK—Public transportation (excluding taxicab)	20.55	37.55	5.00	0.00	0.00	23.00	341.00	23.00
Estimate; COMMUTING TO WORK—Walked	42.34	94.02	22.00	0.00	7.75	45.00	1747.00	37.25
Estimate; COMMUTING TO WORK—Worked at home	63.17	67.40	45.00	0.00	18.00	84.25	646.00	66.25
Estimate; COMMUTING TO WORK—Mean travel time to work (minutes)	22.76	4.95	22.40	8.40	19.20	25.70	44.40	6.50

	Mean	St. Dev.	Median	Min	1st Quartile	3rd Quartile	Max	Inter Quartile Range
Percent; INDUSTRY—Agriculture, forestry, fishing and hunting, and mining	1.50	2.46	0.50	0.00	0.00	1.90	18.10	1.90
Percent; INDUSTRY—Construction	5.92	3.45	5.40	0.00	3.40	7.90	21.70	4.50
Percent; INDUSTRY—Manufacturing	18.32	8.80	16.75	0.00	12.20	22.60	59.90	10.40
Estimate; INCOME AND BENEFITS (IN 2012 INFLATION-ADJUSTED DOLLARS)—Median household income (dollars)	47996	18790	46029	5369	34792	58089	155862	23297
Estimate; INCOME AND BENEFITS (IN 2012 INFLATION-ADJUSTED DOLLARS)—Mean household income (dollars)	58987	22575	56362	6516	43670	68633	208922	24963
Percent; INCOME AND BENEFITS (IN 2012 INFLATION-ADJUSTED DOLLARS)—With Food Stamp/SNAP benefits in the past 12 months	13.10	11.07	10.00	0.00	5.10	18.03	100.00	12.93
Estimate; INCOME AND BENEFITS (IN 2012 INFLATION-ADJUSTED DOLLARS) —Median family income (dollars)	57344	21436	55790	4833	43213	68750	171318	25537
Estimate; INCOME AND BENEFITS (IN 2012 INFLATION-ADJUSTED DOLLARS) —Mean family income (dollars)	67995	25776	64702	10186	50989	79474	225358	28485
Estimate; INCOME AND BENEFITS (IN 2012 INFLATION-ADJUSTED DOLLARS) —Per capita income (dollars)	23402	8430	22336	1573	18147	27264	69800	9117
Percent; HEALTH INSURANCE COVERAGE— - With health insurance coverage	84.90	7.71	86.00	21.90	80.80	90.20	100.00	9.40
Percent; PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL—All families	13.48	12.30	9.70	0.00	5.20	17.60	100.00	12.40

	Mean	St. Dev.	Median	Min	1st Quartile	3rd Quartile	Max	Inter Quartile Range
Percent; PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL—All families—With related children under 18 years	20.36	16.48	16.50	0.00	8.20	28.60	100.00	20.40
Estimate; HOUSEHOLDS BY TYPE—Total households	1644	726	1531	0	1163	2049	6361	886
Percent; HOUSEHOLDS BY TYPE—Family households (families)	65.52	13.33	67.40	0.00	59.30	74.50	98.30	15.20
Percent; HOUSEHOLDS BY TYPE—Family households (families) —With own children under 18 years	29.16	8.31	29.10	0.00	24.50	33.90	66.20	9.40
Percent; HOUSEHOLDS BY TYPE—Family households (families)—Married-couple family	47.98	16.83	50.05	0.00	36.40	61.03	97.10	24.63
Percent; HOUSEHOLDS BY TYPE—Family households (families)—Married-couple family—With own children under 18 years	18.79	8.62	18.60	0.00	13.00	23.90	61.80	10.90
Percent; HOUSEHOLDS BY TYPE—Family households (families)—Female householder, no husband present, family	13.00	8.10	10.85	0.00	7.50	16.30	53.40	8.80
Percent; HOUSEHOLDS BY TYPE—Nonfamily households	34.21	13.02	32.45	0.00	25.50	40.50	100.00	15.00
Estimate; HOUSEHOLDS BY TYPE—Average household size	2.52	0.35	2.52	0.00	2.33	2.71	4.28	0.38
Estimate; HOUSEHOLDS BY TYPE—Average family size	3.09	0.35	3.06	0.00	2.92	3.24	5.02	0.32
Percent; EDUCATIONAL ATTAINMENT—Less than 9th grade	4.58	4.55	3.50	0.00	1.90	5.80	63.60	3.90
Percent; EDUCATIONAL ATTAINMENT—9th to 12th grade, no diploma	9.81	6.05	9.00	0.00	5.60	12.90	52.80	7.30
Percent; EDUCATIONAL ATTAINMENT—High school graduate (includes equivalency)	35.88	10.26	37.40	0.00	30.80	43.10	58.50	12.30
Percent; EDUCATIONAL ATTAINMENT—Some college, no degree	20.94	4.93	20.80	0.00	17.90	23.90	50.40	6.00
Percent; EDUCATIONAL ATTAINMENT—Associate's degree	7.43	2.89	7.40	0.00	5.50	9.30	20.30	3.80

	Mean	St. Dev.	Median	Min	1st Quartile	3rd Quartile	Max	Inter Quartile Range
Percent; EDUCATIONAL ATTAINMENT—Bachelor's degree	13.46	8.66	11.10	0.00	7.10	17.60	54.50	10.50
Percent; EDUCATIONAL ATTAINMENT—Graduate or professional degree	7.71	7.36	5.55	0.00	3.28	9.40	59.00	6.13
Percent; EDUCATIONAL ATTAINMENT—Percentage high school graduate or higher	85.42	9.78	87.10	0.00	81.18	91.90	100.00	10.73
Percent; EDUCATIONAL ATTAINMENT—Percentage bachelor's degree or higher	21.17	14.93	16.65	0.00	11.20	26.80	84.40	15.60
Percent; VEHICLES AVAILABLE—Occupied housing units—No vehicles available	7.88	8.28	5.10	0.00	2.50	10.30	66.30	7.80
Percent; VEHICLES AVAILABLE—Occupied housing units—1 vehicle available	33.86	12.01	33.50	0.00	24.50	42.53	100.00	18.03
Percent; VEHICLES AVAILABLE—Occupied housing units—2 vehicles available	37.31	9.78	38.40	0.00	31.70	43.40	71.10	11.70
Percent; VEHICLES AVAILABLE—Occupied housing units—3 or more vehicles available	20.68	10.28	19.20	0.00	12.30	28.60	55.20	16.30
Percent; VEHICLES AVAILABLE—Occupied housing units—3vehicles available	14.45	6.92	14.00	0.00	9.10	19.63	34.60	10.53
Percent; VEHICLES AVAILABLE—Occupied housing units—4 or more vehicles available	6.23	4.37	5.50	0.00	2.90	8.80	26.80	5.90

Appendix B. Spatial Analysis of Traffic Stream Composition

Semi-Variogram Comparison: Interstates

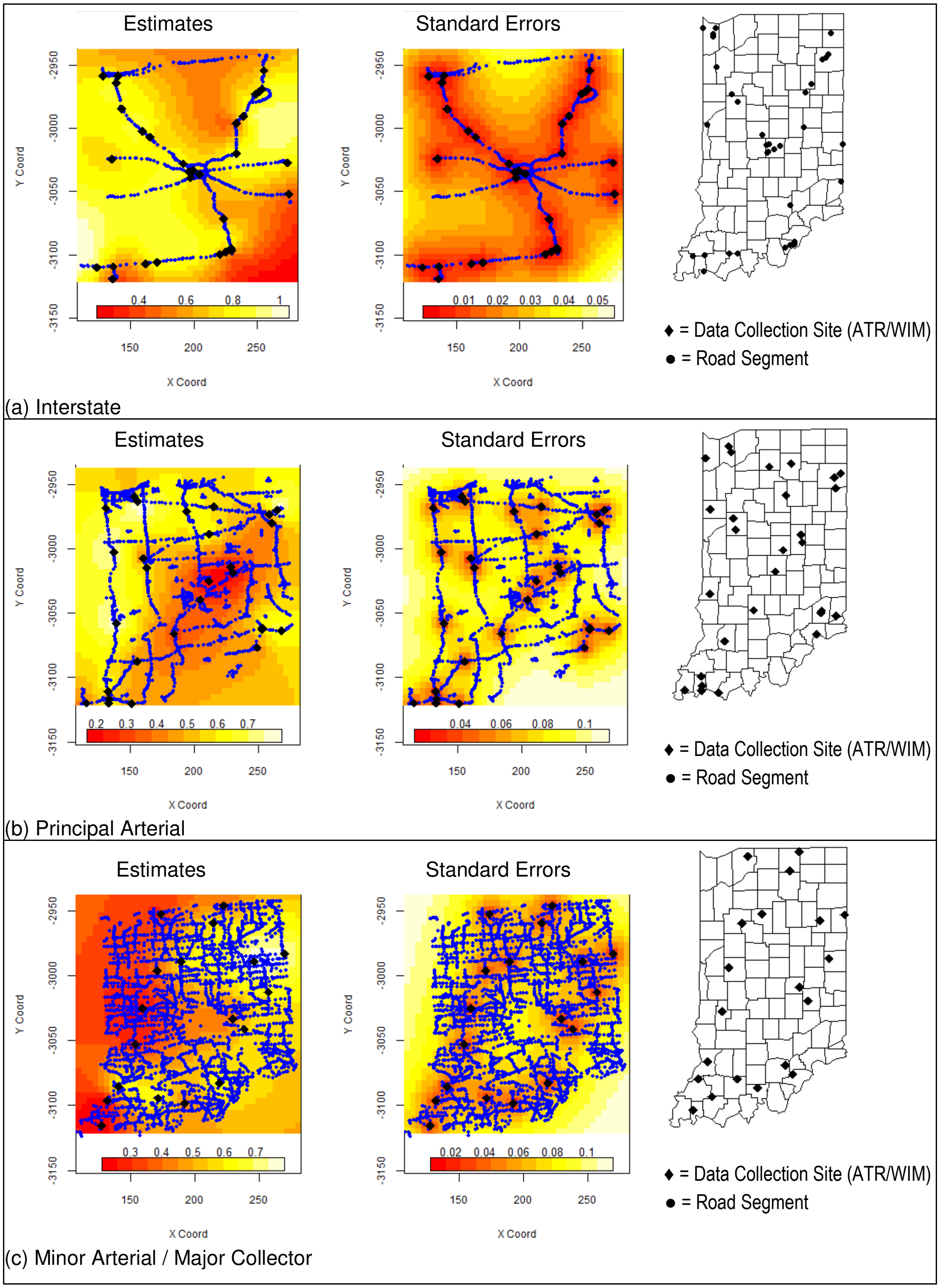
Reference	Estimation Methodology	Covariance Model	Kappa	Nugget	Range (miles)	Partial Sill	MSPE
——	WLS	Exponential	0.5	0.0046	59.91	0.0068	0.012
——	WLS	Matérn	1	0.0069	400.1	0.010	0.014
– – –	ML	Exponential	0.5	0.000	20.49	0.010	0.011
– – –	ML	Matérn	1	0.000	20.49	0.010	0.011

Semi-Variogram Comparison: Principal Arterials

Reference	Estimation Methodology	Covariance Model	Kappa	Nugget	Range (miles)	Partial Sill	MSPE
——	WLS	Exponential	0.5	0.019	59.91	0.017	3.96e-4
——	WLS	Matérn	1	0.015	27.99	0.019	3.85e-4
– – –	ML	Exponential	0.5	0.000	2.60	0.032	4.11e-4
– – –	ML	Matérn	1	0.021	84.49	0.011	3.73e-4

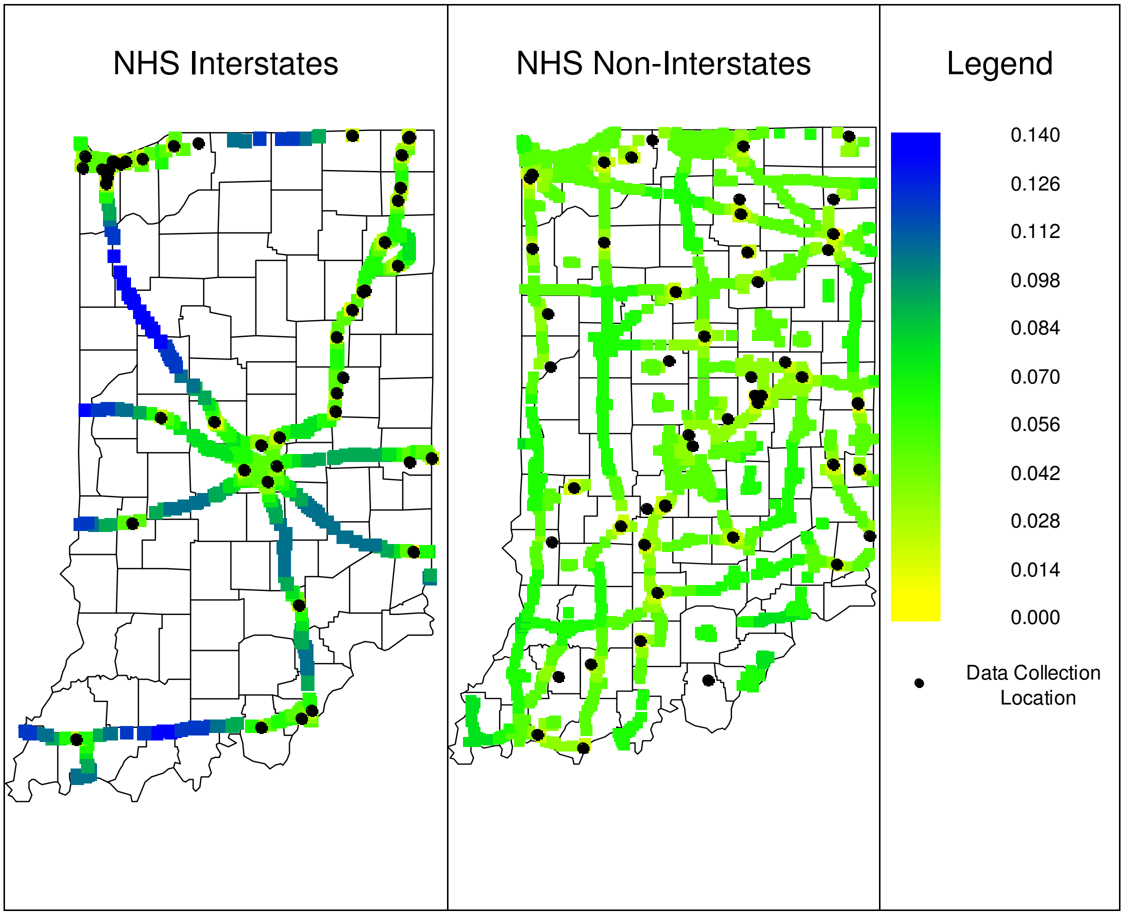
Semi-Variogram Comparison: Minor Arterial/Major Collector

Reference	Estimation Methodology	Covariance Model	Kappa	Nugget	Range (miles)	Partial Sill	MSPE
——	WLS	Exponential	0.5	0.025	149.8	0.012	0.026
——	WLS	Matérn	1	0.025	400.7	0.025	0.034
– – –	ML	Exponential	0.5	0.000	43.80	0.031	0.033
– – –	ML	Matérn	1	0.017	88.30	0.013	0.051

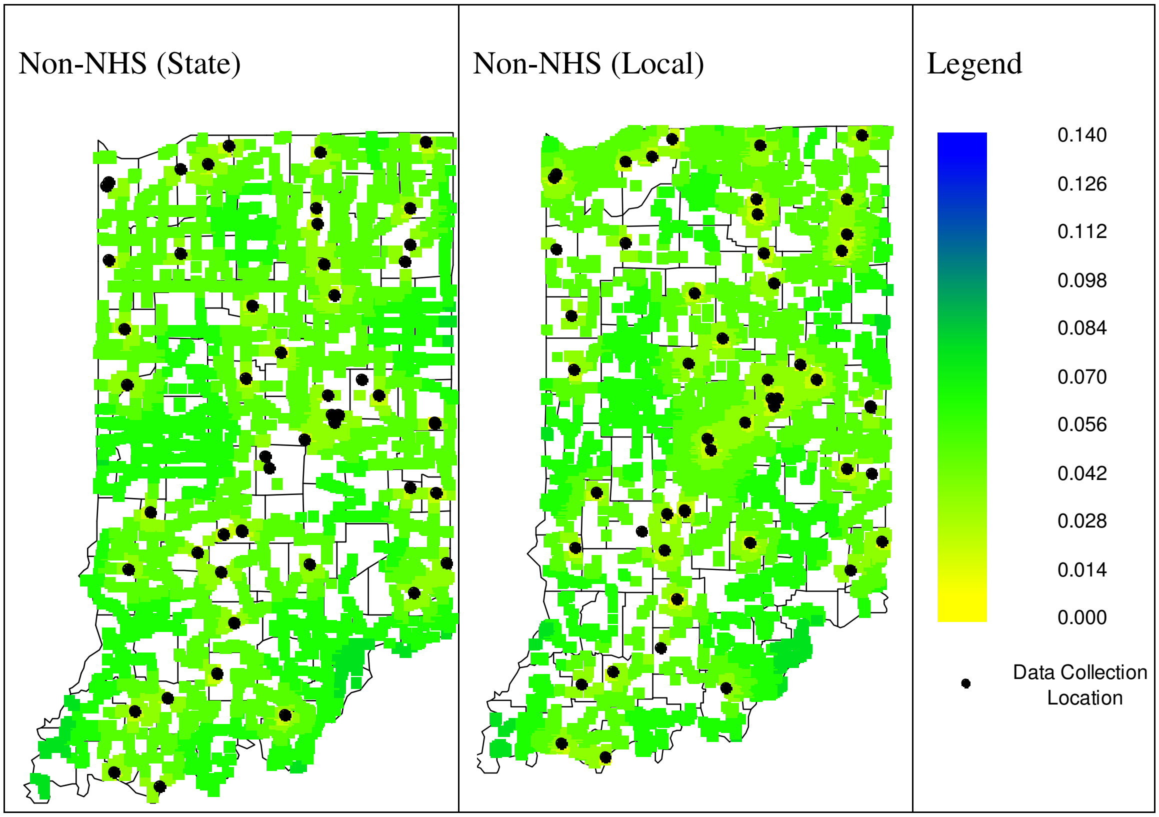


Estimates and Standard Errors for (a) Int. (b) Pr. Art., and (c) Min. Art. / Maj. Col. (coordinates are in miles)

Appendix C. Spatial Analysis of Out-of-State VMT



Standard Errors: Percentage of Passenger Vehicle VMT by Out-of-State Drivers on NHS



Standard Errors: Percentage of Passenger Vehicle VMT by Out-of-State Drivers on Non-NHS Roadways

VITA

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Awards and Honors

Indiana ITE Edward J. Cox Memorial Scholarship, 2014–2015

IRF Student Essay Competition Winner, 2014

Purdue University Eldon J. Yoder Memorial Award, 2014

Purdue University Interdisciplinary Excellence Award, 2014

Purdue University Ross Fellow, 2009–2010

Northeastern University Dean Scholarship, 2003–2007

Northeastern University Metcalf and Eddy Scholarship, 2005

Northeastern University Legacy/Merit Scholarship, 2003

PUBLICATIONS

Refereed Journal Papers

1. Volovski, M., (2015). Funding for Highway Asset Construction and Maintenance: Sustainable Alternatives to the Traditional Gas Tax. IRF Examiner (in print).

2. Volovski, M., Liao, T., Dojutrek, M.S., Labi, S. (2014). Using Kriging Estimation to Enhance Geospatial Climate Data Integrity for Infrastructure Management. Transportation Research Record (in print).

3. Dojutrek, M.S., Volovski, M., Labi, S. (2014). Elemental Decomposition and Multi-Criteria Method for Valuing Transportation Infrastructure. Transportation Research Record (in print).

4. Murillo-Hoyos, J., Volovski, M., Labi, S. (2014). An Econometric Analysis of Purchase Cost for Public Transportation Rolling Stock. Transportmetrica (A) (under review).

5. Anastasopoulos, P. Ch., Volovski, M., Labi, S. (2013). Preservation: Are "Public Private Partnerships" Cutting Costs? Pavement Preservation Journal 6(3), Fall 2013 Issue, 33-35.

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7. Ahmed, A., VanBoxel D., Volovski, M., Anastasopoulos, P., Labi, S., Sinha, K. (2011). Using Lagging Headways to Estimate Passenger Car Equivalents on Basic Freeway Sections. Journal of Transportation of the Institute of Transportation Engineers, Issue (1), vol. (2).

Selected Invited Talks and Conference Proceedings

1. Volovski, M., Saeed, T., Labi, S., (2015). Econometric Analysis of Steel Bridge Construction Costs, 8th International Symposium on Steel Bridges, Istanbul, Turkey.

2. Saeed, T., Volovski, M., Murillo-Hoyos, J., Labi, S., (2015). A Review of the Impacts of Driverless Vehicle Operation on the Roadway Infrastructure, 1st International Conference on Mechanical and Transportation Engineering (ICMTE '15) Kuala Lumpur, Malaysia.

3. Volovski, M., Labi, S., (2014). Prediction of Routine Highway Expenditures—Accounting for Spatial and Temporal Heterogeneity using Random-Effects Panel-Data Modeling, 93rd Annual Meeting of Transportation Research Board, Washington, DC.

4. Volovski, M., Liao, T., Labi, S. (2014). Using Kriging Estimation to Enhance Climate Data for Transportation Asset Management, presented at the 93rd Annual Meeting of Transp. Research Board, Washington, DC.

5. Volovski, M., Labi, S. (2013). Using Kriging Estimation Techniques to Enhance Climate Data for Transportation Asset Management, 9th Annual Inter-University Symposium on Infrastructure Management (AISIM), Berkeley, CA.

6. Anastasopoulos, P.Ch., Islam, M., Volovski, M., Powell, J., Labi, S. (2011). Comparative Evaluation of Public-Private Partnerships in Roadway Preservation, 90th Annual Meeting of Transportation Research Board, Washington, DC.

7. Volovski, M., (2011). Average Annual Maintenance Expenditure (AAMEX) Modeling for Indiana Highway Assets: A Statistical and Econometric Analysis of the Effect of an Asset's Age on Expected Maintenance Costs, Proceedings, Mid-Continent Transportation Research Symposium in Ames, IA.

8. Ahmed, A., Volovski M., Agbeli, B., Labi, S., (2011). Modeling Vehicle Class Lagging Headways for Estimation of Passenger Car Equivalent: A Comparative Analysis between 3SLS and SURE Modeling Approaches, Mid-Continent Transportation Research Symposium, Ames, IA.

9. Ahmed, A., Volovski, M., Anastasopoulos, P., Labi, S., Sinha K., (2011). Passenger Car Equivalents for Basic Freeway Segments Based on Lagging Headways: Some New Evidence using a System of Equations Approach, 52nd Annual Transportation Research Forum, Long Beach, CA.

10. Anastasopoulos, P.Ch., Islam, M., Volovski, M., Powell, J., Labi, S. (2011). Comparative Evaluation of Public-Private Partnerships in Roadway Preservation, 97th Purdue Road School, West Lafayette, IN.

Other Publications

1. Volovski, M., Econometric Models for Pavement Routine Maintenance Expenditure, M.S. Thesis, Purdue University, 2011.

Technical Reports

1. Volovski, M., Bardaka, E., Zhang, Z., Agbelie, B., Labi, S., Sinha, K., Indiana State Highway Cost Allocation and Revenue Attribution Study and Estimation of Travel by Out-of-State Vehicles on Indiana Highways, Joint Transportation Research Program, Indiana DOT and Purdue University, 2015.

2. Volovski, M., Arman, M., Labi, S., Developing Statistical Limits for Using the Light Weight Deflectometer (LWD) in Construction Quality Assurance, (FHWA/IN/JTRP-2014/10), Joint Transportation Research Program, Indiana DOT and Purdue University, 2014.

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4. Ahmed, A., Volovski, M., VanBoxel, D., Labi, S., Sinha, K., Truck Travel Characteristics as an Indicator of System Condition and Performance, (FHWA/IN/JTRP-2011/07), Joint Transportation Research Program, Indiana DOT and Purdue University, 2011.